CONFIGURATIONS OF RISK FACTORS FOR

POOR PARENTAL TREATMENT

ENGAGEMENT

by

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ABSTRACT

Behavioral parent training is an effective treatment for many child behavior problems; however, low parent attendance and engagement has been a chronic barrier to its successful implementation. Previous research identified a number of risk factors that were predictive of low engagement in parent training. The present study tested whether these risk factors were valid predictors in a targeted prevention sample using latent class analysis and a binary segmentation procedure to identify meaningful sub-groups within the sample. Although the latent class analysis did not identify meaningful classes which predicted attendance, the binary segmentation procedure resulted in six mutually exclusive groups. These groups were classified based on social support and stressful life events, and group membership significantly predicted attendance at parent training. The validity of these predictors was further supported by a backward stepwise regression. Other frequently studied predictors, such as income, did not discriminate within the sample. These findings suggest that the risk factors for low engagement and participation in targeted prevention parenting interventions may be different from the risk factors for treatment seeking samples.

DEDICATION

This thesis is dedicated to my mom, who has always been my biggest fan, and to my grandparents, who have never stopped believing in me.

This thesis is also dedicated to the memory of my cousin, Vicki Eikenburg, who made me promise to stay focused and never give up.

LIST OF ABBREVIATIONS AND SYMBOLS

α Cronbach’s alpha: an index of internal consistency

df Degrees of freedom: the number of values in the final calculation of a statistic that are free to vary after certain restrictions have been placed on the data

F Fisher’s *F* ratio: a ration of two variances

M Mean: the sum of a set of items divided by the number of items within the set

N Sample size of group

p Probability: chance of occurrence under the null hypothesis of a value more extreme than the observed value

r Pearson’s *r*: value of correlation

r^2 The coefficient of determination: the proportion of variability accounted for by a model

SD Standard Deviation: value of variation from the mean

t Value of the *t*-test

$<$ Less than

$=$ Equal to

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INTRODUCTION

Configurations of Risk Factors for Poor Parental Treatment Engagement

Treatment retention for families of children with disruptive behavior problems is consistently problematic; 40-60% of families in outpatient programs prematurely terminate treatment (Kazdin, 1996; Kazdin, Holland, Crowley, & Breton, 1997). Dropping out of treatment is particularly problematic because the families who drop out of treatment are often the ones who are the most severely impaired (Kazdin, Mazurick, & Siegel, 1994) Furthermore, families who prematurely terminate treatment are significantly less likely to improve, compared to those who complete treatment (Prinz & Miller, 1994).

Simply retaining families in treatment is insufficient for meaningful change; results from a comprehensive, early intervention for high-risk kindergarteners with conduct problems (Fast Track) found that the quality of participation in the parent training groups was predictive of treatment response, and attendance was not (Nix, Bierman, McMahon, & The Conduct Problems Prevention Research Group, 2009). Terms such as treatment engagement, participation, adherence and compliance have often been used interchangeably, and are operationalized differently across studies (Staudt, 2007). Engagement typically refers to families attending treatment sessions and completing the treatment protocol, but it can also include components such as participation in session, completion of homework, and progress towards treatment goals (Staudt, 2007). The present study conceptualizes treatment engagement as attendance and participation in treatment sessions.

Family Characteristics Which Predict Treatment Engagement

Existing literature on treatment engagement has identified a number of family characteristics that are predictors of poor treatment engagement and early termination of treatment. The variables that will be examined by the present study are: socioeconomic disadvantage, difficult family situations, low social support, stressful life events, and caregiver depression. These variables have all been identified as significant risk factors for dropping out of treatment (e.g., Kazdin, Holland, & Crowley, 1997; Kazdin, Holland, Crowley, et al., 1997; Kazdin, Mazurick, & Bass, 1993; Kraemer, Stice, Kazdin, Offord, & Kupfer, 2001; Staudt, 2007).

Socioeconomic Disadvantage as Predictive of Treatment Engagement

Socioeconomic disadvantage is the most frequently studied risk factor; it has typically been shown to predict lower treatment engagement, possibly due to transportation difficulties, or being unable to take time from work for treatment sessions (Kazdin, Holland, & Crowley, 1997). However, not every study has found socioeconomic disadvantage to predict poor engagement; Gould, Shaffer and Kaplan (1985) found no sociodemographic variables to differentiate completers from dropouts. In their sample of families receiving psychiatric clinic services, only caregiver symptomology predicted dropout (Gould, et al., 1985). Likewise, Frankel and Simmons (1992) found that only parental psychopathic distortion predicted treatment drop-out; they found no relationship between socioeconomic status and treatment drop-out.

In a study of engagement in preventative interventions, Spoth, Goldberg, and Redmond (1999) found that higher rates of attrition for socioeconomically disadvantaged families were better accounted for by differences in parental educational attainment. They concluded that financial hardship was not central to participation, and suggested that more highly educated parents have more favorable attitudes regarding participation in prevention programs (Spoth, et al., 1999).

Given these inconsistent findings, educational attainment and income may each be linked to different configurations of risk factors which have distinct trajectories of treatment engagement. Therefore, the present study will treat parental educational attainment and household income as separate predictors, rather than using a composite measure of socioecomomic status (e.g., Hollingshead, 1975).

Family Circumstances and Social Support as Predictive of Treatment Engagement

Another risk factor for poor treatment engagement is difficult family circumstances; families with single parents, and young parents, are at higher risk for poor treatment engagement (Kazdin & Mazurick, 1994; Staudt, 2007). Kazdin and Mazurick (1994) found that young parents, and single parents, were significantly more likely to drop out of treatment very early on. However, both single parent status, and parental age were significantly correlated with socioeconomic status, which was also a significant predictor. Thus, it may be that the socioeconomic status accounted for the poor treatment engagement, rather than being a single or young parent.

Being a single parent also puts a greater burden of care on the custodial parent, and as such, may uniquely predict engagement. Families with more than one adult in the home keep more mental health appointments for their children; sharing the burden of care giving appears to be important for ongoing mental health service use (McKay, Pennington, Lynn, & McCadam, 2001).Therefore, single parent versus multiple-parent household, and parental age, will be examined as predictors in the present study.

A related variable that will be examined is the degree of social support provided to the primary caregiver; high social support has been associated with keeping initial mental health appointments, as well as improved outcomes in parent training (Staudt, 2007). Parents enrolled in a comprehensive, early intervention for high-risk kindergarteners with conduct problems (Fast Track) benefitted from increased social support, relative to control parents: By increasing the social support of previously isolated parents, treatment outcomes were improved (The Conduct Problems

Prevention Research Group, 2002). These findings demonstrate that social support is important for treatment outcome, and that lack of adequate social support is a barrier to treatment engagement. Therefore, low social support will be examined as a predictor of engagement; however, extremely high social support could also potentially predict poor treatment engagement. Families with a strong support system may not benefit as much from the social support network inherent in group parent training classes, and could be less motivated to attend. This is a possibility which has not been addressed in the literature to date, despite "social support" being a key reason for conducting parent training in groups. Because the analytic strategy used requires dichotomous predictor variables, the present study was able to look at whether high social support could be a potential risk factor.

Stressful Life Events as Predictive of Treatment Engagement

Experiencing a number of stressful life events has been inconsistently associated with poor treatment engagement. Stressful life events refers to the family experiencing circumstances such as a separation or divorce, the loss of a caretaker's job, a death in the family, legal difficulties, eviction, or serious injuries. Some research has indicated that a higher number of stressful life events predicted very early drop out from treatment, however, it may be that socioeconomically disadvantaged families experience more stressful life events and their socioeconomic disadvantage better accounts for their poor treatment engagement (Kazdin, Holland, & Crowley, 1997; Kazdin & Whitley, 2003). The experience of stressful life events is associated with higher parental stress, which is typically a significant predictor of early treatment termination, and fewer treatment sessions attended, especially for lower income families (Kazdin & Whitley, 2003; McKay, et al., 2001). Although stressful life events and higher parental stress typically predict lower treatment engagement, some research has found that caregivers experiencing more stressful life events and stress as a result of their child's problems have fewer gaps in care and seek out more mental health services (Ana María Brannan, Heflinger, & Foster, 2003). These inconsistent patterns suggest that some stressful life events and parental stress may be important for treatment engagement, perhaps because they increase parent motivation (Kazdin & Whitley, 2003). Consistent with previous research, the present study conceptualized stressful life events as one total score, which represents the number of such events experienced (Kraemer, et al., 2001; Nock & Kazdin, 2001; Nock & Photos, 2006).

Caregiver Depression as Predictive of Treatment Engagement

Parental psychopathology is routinely associated with worse treatment engagement and more missed sessions, especially parental depression (McKay, et al., 2001). Parental depression is among one of the most studied risk factors for poor treatment engagment. Mothers with depressive symptomology are less likely to follow through with treatment recommendations, and they percieve more barriers to interacting with mental health professionals, and the mental health care system (Anderson, et al., 2006). Caregiver depression consistently predicts worse treatment attendance and worse treatment outcomes for parents of children with disruptive behavior disorders (Chronis, et al., 2007). Consequently, the present study will evaluate parental depression as a risk factor for less treatment engagement.

Current Investigation

Although prior research has successfully identified some seemingly salient predictors for poor treatment engagement, these predictors have only been studied individually, or aggregated into a cumulative risk factor. This approach assumes that all risk factors are equally influential, and does not consider that variations in the configurations of these risk factors could predict variations in patterns of treatment compliance and engagement. These types of variable-centered approaches to analysis rely on the assumption that samples are relatively homogenous, and do not provide information on how particular risk factors may operate differently for individual participants (Mendez, Carpenter, LaForett, & Cohen, 2009). The use of such approaches may contribute to the lack of consistency across studies in identifying risk factors responsible for low engagement

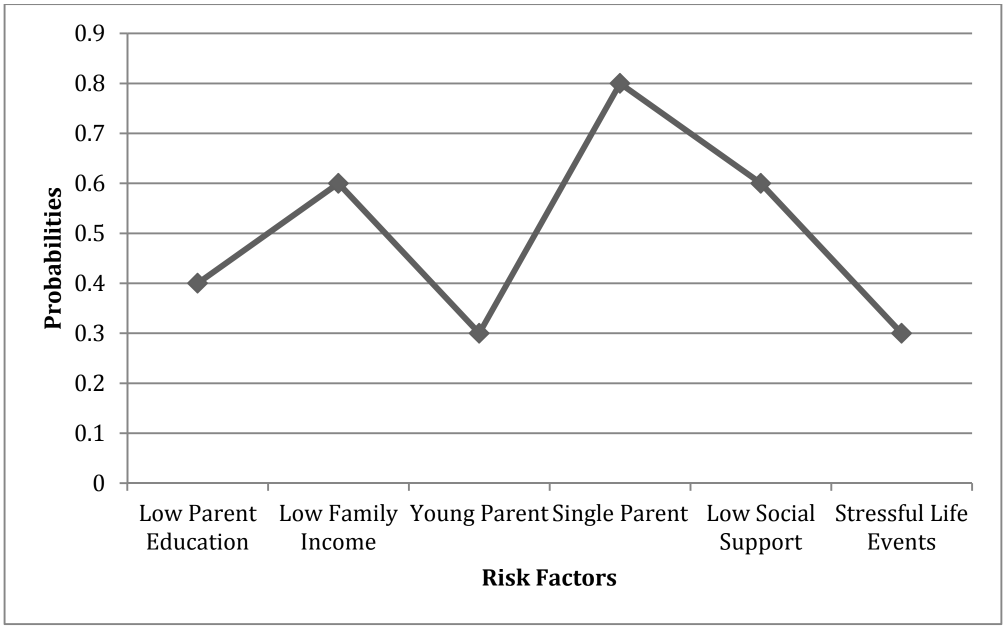
(Kazdin, et al., 1993). The present study addresses this gap in the literature by using a person-centered approach to analysis which allows for a more fine-grain analysis of how individual differences in risk factors may affect engagement (Mendez, et al., 2009).

The present study will address this gap in the literature by first identifying latent classes in the sample, and secondly by testing the relationship between membership in these classes and treatment engagement over time. The specificity of the risk factors for each latent class will provide a richer understanding of why families fail to complete treatment. This will hopefully lead to the development of interventions that better target those identified risk factors and increase treatment engagement for at-risk families (Kazdin, et al., 1993). The present study is an exploratory analysis; to date no studies have used risk factors for low treatment engagement to identify latent classes in the sample. Therefore, there are no hypotheses regarding which specific configurations of risk factors will identify the latent classes. One possible configuration of risk factors is presented in Figure 1 as an example of what a high-risk latent class might look like; this example is based upon the most consistent predictors for poor treatment engagement as reviewed previously.

There are two primary research questions this study is designed to address: Are there meaningfully distinct classes, or configurations of risk factors, and if so, how are these classes associated with treatment engagement? If the latent class analysis identifies meaningful configurations of risk factors, then the latent classes with the highest risk should have the lowest mean levels of engagement.

Figure 1

Example: Possible High Risk Class



Notes: An example of a possible high risk class, following the planned latent class analysis. Endorsement probabilities on the Y axis indicate the likelihood that risk factor will be present for a given family.

METHODOLOGY

Participants

The data that will be used for the present study was collected as part of a larger investigation of a school-based conduct problems prevention program, the Coping Power Program (Lochman, Wells, & Lenhart, 2008). The larger study included 240 participants, half of whom were randomly assigned into the intervention condition, and the remaining half was randomized to a no treatment control group. Only data from the intervention participants will be used in the present study because the control participants did not receive treatment and therefore no engagement data was collected. The intervention group received the Coping Power Program, which is a manualized cognitive behavioral preventive intervention for youth at risk for behavior problems (Lochman, Wells, & Murray, 2007).

The sample consisted of three cohorts of families recruited over a 3-year period from 10 urban public elementary schools. Families were recruited for participation based on teacher-rated levels of aggressive behavior. The top 30% of fourth graders, a total of 565 children, on teacher ratings of aggression were identified as at-risk for delinquent behavior, and families were contacted at random from this group until each cohort had enrolled 80 participants. Each cohort enrolled 40 control and 40 intervention participants. Of the eligible families, 284 were contacted, and 85% of these families initially agreed to participate. This resulted in the total sample of 240 families; 120 families were randomized to receive the intervention, and 120 families were assigned to the no treatment control. Across both treatment conditions, 64% were boys, and 36% were girls. Sixty-nine percent of the children self-identified as African American, 30% as Caucasian, and 1% as another race or ethnicity. Eighty-seven percent of the children lived with at least one biological parent, and 23% lived with both biological parents. Thirty-seven percent of families reported an annual income under $15,000, with 26% reporting an income between $15,000 and $29,000, 22% between $30,000 and $49,000, and only 15% reported an annual income greater than $50,000. The treatment and intervention groups did not significantly differ on any social or demographic variable at baseline. See table 1 for complete baseline characteristics.

Table 1

Sample Characteristics: Caregivers

Characteristics	*N* (%)	*M*	*SD*
Education			
At least High School or GED	92 (76%)		
Less than High School	29 (24%)		
Income			
>$15K	64 (53%)		
<$15K	57 (47%)		
Marital Status			
Has parenting partner	45 (37%)		
Does not have parenting partner	76 (63%)		
Age at birth of target child (in years)		23.56	5.75
19 or older	98 (81%)		
18 or younger	23 (19%)		
Depression (BDI Score)		8.09	7.10
BDI score ≤ 9	80 (66%)		
BDI score ≥ 10	41 (34%)		
Social Supports		4.52	2.67
3 or more social supports	92 (76%)		
2 or fewer social supports	29 (24%)		
Stressful Life Events		1.83	1.80
2 or fewer stressful life events	84 (69%)		
3 or more stressful life events	37 (31%)		
Parent Training Sessions Attended		3.76	3.58
Session Engagement‡	55	3.57	.90

Notes: Engagement data was not collected in the first cohort, and there was a high rate of missing data in subsequent cohorts.

Procedure

All procedures for the larger study were approved by the Internal Review Board at the University of Alabama, Tuscaloosa. Both parental consent and child assent were obtained before primary data collection began. Data for the present study were collected from the parent/caregiver, and the clinician who lead the parent training sessions. Parent measures were collected in an interview format in the participant's homes; 93% of the families had one of the child's biological parents completing the interviews. Baseline data was collected during the summer before the children entered fifth grade.

Coping Power has both child and parent components, and this version of the program included 24 child group sessions and 10 parent sessions (Lochman, Boxmeyer, Powell, Roth, & Windle, 2006). Each parent group was co-led by two research staff, typically one doctoral-level supervisor, and one master's-level staff member. These clinicians tracked parent attendance at sessions, and rated parent level of engagement at attended sessions. Parent groups included parents and other primary caregivers of children enrolled in Coping Power. Session content focused on improving parents' behavioral management skills, family problem solving, communication, and family cohesion (Lochman, et al., 2006). A number of strategies were used to encourage parental attendance, such as scheduling sessions after 5:00 p.m., providing childcare on site, snacks for parents and child, and compensating parents with small stipends. These strategies were approved by the Institutional Review Board to facilitate treatment engagement and were not felt to be coercive.

Measures

Demographic information. Caregivers completed a demographic questionnaire which collected information regarding the child's living arrangements for the past 30 days; parents were instructed to mark all that apply (e.g., two biological parents, mother only, mother and adult male, grandparents, etc.). This questionnaire also asked the caregivers to classify their relationship to the child (e.g., birth parent, stepparent, adoptive parent, foster parent, etc.), and asked for the age of the caregivers. Caregivers were also asked about their marital status, and whether they received government assistance. Caregivers then rated their gross family income over the past year using a 13-point scale from 0 (earns no income/dependent on welfare) to 12 (earns $100,000 or more).

Additionally, caregivers were asked to list all adults in the household, give their relationship to the target child, their occupation, and highest grade completed in school. Highest grade completed was re-coded using the Hollingshead index to create the education variable (Hollingshead, 1975). The Hollingshead index is a widely used measure of socioeconomic status, and it was used in the present study to demonstrate the present sample is comparable to samples used in other studies of prevention programs (Cirino, et al., 2002). All reported means reflect Hollingshead education scores with a score of four indicating completion of high school or general equivalency diploma (GED).

Social support. Caregivers completed a modified version of the Social Support Questionnaire (SSQ) Short-Form (Sarason, Sarason, Shearin, & Pierce, 1987). This measure asks caregivers to list up to 10 people whom they feel they "can count on for help or support when [they] need it, or when [they] are feeling down in the dumps, or are upset about something" (see Appendix for the modified SSQ used in the present study). Caregivers then rate their satisfaction with the level of help and support they receive from those people using a 6-point Likert-type scale ranging from 1 (very dissatisfied) to 6 (very satisfied). Additionally, caregivers then rate their satisfaction with the support they receive from those people regarding issues with their child, using the same 6-point Likert-type scale. There is no data available on the reliability or validity of the modified SSQ, however, the SSQ long-form (Sarason, Levine, Basham, & Sarason, 1983) and short-form (Sarason, et al., 1987) have both been shown to be valid and highly internally consistent. The long-form has demonstrated an alpha coefficient of .97 (Sarason, et al., 1983).

Life events. Caregivers completed a list of 12 life events that may have impacted the child and family. Caregivers indicate whether the events occurred in their family in the last 12 months; items are scored as yes or no. Life event questionnaires are commonly used in treatment engagement research, and there is no "gold standard" life event measure (Kazdin, 2000; Kazdin, Holland, & Crowley, 1997; Kazdin, Holland, Crowley, et al., 1997; Kazdin & Mazurick, 1994; Kazdin, et al., 1993; Kazdin & Whitley, 2003; Nock & Kazdin, 2005). For the present study, the 12-item life event questionnaire was scored by counting the number of yeses.

Depression. Caregiver depression was assessed with the Beck Depression Inventory (BDI), a well-validated 21-item measure of depressive symptoms (Beck & Steer, 1984; Beck, Ward, Mendelson, Mock, & Erbaugh, 1961). Caregivers are asked to select one response, of four possible choices, that best describes the way they have felt over the past week. Each item is rated on a four-point scale ranging from 0 to 3; each item corresponds to a symptom of depression. The scores of all 21-items are summed to derive an overall score, and higher overall scores indicate more depressive symptoms endorsed. The typical cut-off score for clinical depression is 15; however, a score of ten indicates mild depressive symptoms and being at-risk for major depression (Beck, Steer, & Carbin, 1988). The BDI has been well studied and typically has an internal consistency alpha coefficient of .86 (Beck & Steer, 1984). The BDI has been demonstrated to be a valid and reliable instrument regardless of the gender or ethnic makeup of a population, and correlates well with clinical assessments of depression (Beck, et al., 1988). Cronbach's alpha was equal to .85 in the current sample.

Parent Engagement in Treatment. Parent engagement in treatment was measured by two separate indicators: the number of parent training sessions attended, and the mean clinician-rated level of parent engagement in sessions. Clinicians were instructed to base their ratings on the degree to which parents participated in session, contributed to discussions, and demonstrated positive affect. Homework completion was not considered in ratings of parent engagement because rates of homework completion were low throughout the sample, even for highly engaged families. Engagement was rated on a scale of 0 (*did not attend)* to 5 (*Highly engaged)*; the mean level of engagement for sessions attended was used in all analyses.

Analytic Strategy

Latent class analysis. Latent class analysis (LCA) is a mixed method of analysis which seeks to identify unspecified subsets of related cases (i.e., latent classes) within the data. Each latent class is characterized by a profile of endorsement probabilities for each identified risk factor, and each case is assigned probability for membership in each class (McCutcheon, 1987). Each case was classified according to its most probable class membership.

The primary purpose of performing a latent class analysis is to create a set of latent classes which represent response patterns in the data and determine how prevalent each class is. This analysis also enables the researcher to determine the amount of error associated with each risk factor in establishing these classes. When there is less error associated with a given risk factor, there will be observable differences in the response probabilities between classes. This is referred to as low independence between an observed variable, and the latent variable, and it allows us to reliably predict class membership based on an individual's response on the observed variable. Lower independence indicates less error, and suggests that the latent variable is reflecting true differences in response patterns (Collins & Lanza, 2009).

Typically, LCA uses dichotomous variables for ease of interpretation; classes can then be characterized by the probability of having any given risk factor (Vermunt & Magridson, 2003). Most of the risk factors in the present study were dichotomized using pre-determined cut-points. The cut-point for income was set at $15,000 per year, based on the Department of Health and Human Services poverty guidelines for 2003 (Thompson, 2003). Education was classified as did, or did not, complete high school/GED. Marital status was classified as has a parenting partner (married or cohabitating), or does not have a parenting partner (single, widowed, divorced or separated). Maternal age was classified using the age of the mother at the birth of target child, and mothers were classified as either 18 years old or younger at the birth of the target child, or at least 19 years old. This cut-point was selected based on current research indicating that children born to mothers who are 18 years of age or younger are at significantly greater risk for poor overall adjustment, and behavior problems, including aggression and delinquency (Pianta, López-Hernández, & Ferguson, 1997; Weaver, Borkowski, & Whitman, 2008). Depression was classified as being a risk factor if the individual had a BDI score of ten or greater; ten was used as the cut-point because it indicates a risk for depression in non-clinical samples (Beck, et al., 1988). The two remaining risk factors, stressful life events and social support, were dichotomized using cut-points established by examining the frequency distributions and selecting scorings that identified individuals at or above the 75th percentile on that measure. Using this method, the cut-point for stressful life events identified participants with three or more stressful life events as at risk. Similarly, participants with two or fewer social supports were considered to be at risk.

Latent class models were fitted using Mplus (Muthén & Muthén, 2010). Mplus estimates solution parameters using an iterative method of maximum likelihood and uses random starting values (Jung & Wickrama, 2008; Muthén & Muthén, 2010). This combination of features increases the likelihood of model stability and convergence on a global maximum solution, which is associated with the largest loglikelihood (Jung & Wickrama, 2008).

A set of analyses were conducted to generate the best-fitting latent class model, and models estimating 1-class through 5-class solutions were evaluated. These analyses used the same random starting values, and only varied the number of classes requested in the solution. There is no "gold standard" statistical index used to compare the fit of latent class models, no equivalent of a *p*-value, so multiple criteria are considered to determine the best model-fit (Jung & Wickrama, 2008). These criteria include the 1) Bayesian Information Criterion (BIC), a goodness-of-fit index that considers sample size, number of free parameters, and value of likelihood function, 2) a chi-square (χ^2) test of model fit, 3) likelihood ratio tests for M classes versus M-1 classes (Jung & Wickrama, 2008). Typically, models with lower BIC values fit the data best; however, a "low" BIC value is relative and not absolute. For criterion 2, both the χ^2 and the likelihood ratio chi-square (L^2) were considered for each model. For criterion 3, the Lo, Mendell, and Rubin (2001) likelihood ratio test (LMR-LRT) is the most commonly used statistic; however, the bootstrap likelihood ratio test (BLRT) has been shown to be better indicator of model fit (Jung & Wickrama, 2008). Both the LMR-LRT and the BLRT were considered in the final model selection. Table 4 gives the values for these indicators for all models evaluated.

After the number of classes were identified for the final model, an Analysis of Variance (ANOVA) was conducted to test for mean differences between classes on number of sessions attended and mean level of engagement.

Post Hoc Analyses. Several post hoc analyses were conducted to evaluate the validity of the identified risk factors and analytic strategy. Backward stepwise linear regression was used to test the validity of the identified risk factors as predictors, and a binary segmentation procedure was used as an alternative classification method to LCA.

Backward stepwise regression. All seven risk factors were entered in a single step into the backward stepwise linear regression which generated a total of eight models. The risk factor which explained the least amount of variance was removed first, and one additional risk factor removed for every subsequent model, with model 7 having only one predictor, and model 8 having no predictors and reflecting the constant.

Binary segmentation procedure: SEARCH. MicrOsiris was used to run a binary segmentation program called SEARCH (Van Eck & Van Eck, 2011a). Binary segmentation procedures are a family of statistical "tree" techniques used to create mutually exclusive subgroups within the data set to develop a predictive model for a dependent variable (Morgan, 2005). The advantages of binary segmentation are numerous, although there are several notable weaknesses. Binary segmentation, in contrast to LCA, does not necessarily use every predictor entered into the analysis; it only uses the predictors which significantly reduce error variance, and the sample may be split on the same predictor more than once (Van Eck & Van Eck, 2011b). The greatest theoretical advantage of binary segmentation procedures is that if a predictor is never used for a split, then hypothetically it is not meaningful to the entire sample or any subgroup and can be discarded (Morgan, 2005). With regression, correlated predictors can significantly increase the error; with binary segmentation procedures, splitting on one predictor will reduce the likelihood of a split on highly correlated other predictors (Morgan, 2005). Disadvantages to binary segmentation procedures are that these are techniques that work best on very large samples, and the earliest splits tend to be more stable than later splits because they are based on a larger sample. Also, binary segmentation procedures are not widely used in psychological research, and have not been previously been applied to research questions relating to treatment engagement.

SEARCH differs from other binary segmentation procedures by focusing on a maximum reduction in error variance, relative to the starting error variance, rather than on traditional tests of significance. The question SEARCH asks is "what dichotomous split on which single predictor variable will give us a maximum improvement in our ability to predict values of the dependent variable?" (Van Eck & Van Eck, 2011b, p. 241). At each subsequent step in the procedure, the split into two new subgroups accounts for more of the variance than any other possible split (Morgan, 2005). This was an exploratory analysis, so all the risk factors were entered in as select predictors, which means that all predictors were considered at each step of the SEARCH splitting procedure (Van Eck & Van Eck, 2011b). SEARCH was run using continuous or ordinal data when possible; the exception is marital status remained a dichotomous predictor variable.

Following the use of SEARCH to generate an exploratory model, an ANOVA was run to test for group differences in attendance at parent training. It was not possible to run the SEARCH program with the clinician-rated engagement as the dependent variable because the potential bias in favor of predictors with more response options increases with a decrease in degrees of freedom, and engagement data was available for less than half the sample.

RESULTS

Relationships Between Variables

Pearson correlations showed significant inter-correlation between variables. These initial analyses used continuous items, except for marital status, as noted below.

Income and education were positively correlated, r (N=121) =.27, p<.01. Both income and education were positively correlated with age, and negatively correlated with depression; see table 2 for complete results. None of the identified risk factors was significantly correlated with total attendance at parent training, although there was a trend towards attendance being positively correlated with income (p=.09). Attendance and mean engagement were significantly positively correlated; participants who attended more sessions were rated as being more engaged (r=.37, p<.01). None of the risk factors was significantly correlated with engagement.

Marital status was not included in these correlations because it was coded as a categorical variable; t-tests were conducted to test the relationship between marital status and the other variables. There was a significant between-groups difference for depression, t (114.71) =2.68, p<.01, equal variances not assumed (Levene's F=7.91, p<.01). Parents with parenting partners reported significantly lower mean levels of depression (M=6.07, SD=5.50) than parents without a parenting partner (M=9.29, SD=7.68). Married or cohabitating parents also had a significantly higher mean level of education than single parents (M=4.67, SD=.98 and M=3.92, SD=.96), t (119) =-4.10, p<.01. See table 3 for complete results.

Table 2

Correlations Among Study Variables

	Age	Income	Education	Depression	Social Support	Life Events	Attendance
Income	.27**						
Education	.24**	.46 **					
Depression	-.20*	-.28 **	-.28 **				
Social Support	.04	.11	.21 *	-.08			
Life Events	-.12	-.10	-.07	.24 **	.06		
Attendance	.10	.16 †	.08	-.07	.15	.14	
Engagement	-.03	.05	.16	-.05	.22	.20	.37**

Notes: N=121
***p< .01 *p<.05* †*p*<.10

Table 3

Relationship of Marital Status to Other Study Variables: t-tests

	M	*SD*	*t*
Age at birth of target child			-1.88
Has parenting partner	24.86	6.05	
Does not have parenting partner	22.81	5.47	
Income			-7.46**
Has parenting partner	6.16	3.05	
Does not have parenting partner	2.58	2.20	
Education			-4.10**
Has parenting partner	4.67	.98	
Does not have parenting partner	3.92	.96	
Depression			2.46*
Has parenting partner	6.07	5.49	
Does not have parenting partner	9.29	7.68	
Social Support			-.04
Has parenting partner	4.53	2.74	
Does not have parenting partner	4.51	2.65	
Stressful Life Events			.58
Has parenting partner	1.71	1.93	
Does not have parenting partner	1.91	1.72	
Total Attendance			-.48
Has parenting partner	3.98	3.83	
Does not have parenting partner	3.64	3.44	
Engagement			-.65
Has parenting partner	3.68	.57	
Does not have parenting partner	3.51	1.04	

Notes: N=121
***p< .01 *p<.05* †*p*<.10

Latent Class Analyses and ANOVA

The 2-class model reviewed had the lowest BIC (1012.01), and had a significant χ^2 value of 163.67 (p<.01), which both indicate the best model fit. The 2-class model also had a significant LMR-LRT, 73.2 (p<.01), and a significant BLRT, 75.15 (p<.01), both of which indicate the 2-class model fits the data significantly better than the 1-class model. However, because the BIC sometimes underestimates the true number of latent classes, the 3-class model is also reviewed (Copeland, Shanahan, Jane Costello, & Angold, 2009). The indicators for models estimating 1-class through 5-class solutions are in listed in table 4.

Table 4

Indicators of Model Fit for 1-Class Through 5-Class Solutions

Model	*df*	BIC	Sample size adjusted BIC	L^2 LRT	χ^2	LMR-LRT	BLRT
1-Class	120	1048.79	1026.67	167.11 **	228.70 **		
2- Class	112	1012.01	964.59	91.96	163.67 **	73.2 **	75.15 **
3- Class	104	1031.80	959.08	73.39	104.62	18.11 *	18.58
4- Class	96	1059.86	961.85	63.08	80.14	10.05	10.31
5- Class	88	1088.07	964.77	52.92	55.68	9.90 **	10.15

*Notes: **p< .01 *p<.05*

2-class model. The sample was almost evenly divided; class 1 had 60 participants, and class 2 had 49 participants. These classes differed most from each other on marital status and income, although there were also differences in education and depression. Most of the participants in class 1 did not have a parenting partner (90%), and 78% had an annual income below the poverty line. In contrast, 71% of the participants in class 2 had a parenting partner, and 92% were above the poverty line. All the participants in class 2 completed high school or a GED, and only 11% were at risk for depression. More of the participants in class 1 were at risk for depression (52%), and 43% had not completed high school or a GED.

See table 5 for the complete results in probability scale, and figure 2 for a graph of the probabilities of endorsement for each risk factor, broken down by most likely class membership.

Class 1 had lower mean attendance than class 2 (*M*=3.50, *SD*=3.50 vs. *M*=4.14, *SD*=3.69); however, a one-way ANOVA on the total number of parent training sessions attended did not reveal a main effect for class membership, F (1,107) = .87, p =.35. Figure 3 shows the distribution of attendance for each class; the distributions are similar for both classes. Each class had a similar percentage of participants not attend at all, and similar percentages for attending between one and ten sessions.

Class 1 and class 2 had similar mean levels of engagement (*M*=3.44, *SD*=1.03 vs. *M*=3.73, *SD*= .69), and a one-way ANOVA again failed to reveal a main effect for class membership, F (1, 53) = 1.45, p =.23.

Table 5

Probabilities of Class Membership for Each Risk Factor: 2-Class Model

Risk Factors	Class 1	Class 2
Age at birth of target child (in years)		
19 or older	.70	.94
18 or younger	.30	.06
Marital Status		
Has parenting partner	.10	**.71**
Does not have parenting partner	.90	.29
Stressful Life Events		
2 or fewer stressful life events	.68	.72
3 or more stressful life events	.33	.28
Income		
Earns more than $15,000 a year	.22	**.92**
Earns less than $15,000 a year	**.78**	.08
Education		
At least High School or GED	.57	1.00
Less than High School	.43	.00
Social Supports		
3 or more social supports	.74	.78
2 or fewer social supports	.26	.22
Depression (BDI Score)		
BDI score ≤ 9	.48	.89
BDI score ≥ 10	.52	.11

Figure 2

Probabilities of Endorsement of Each Risk Factor: 2-Class Model

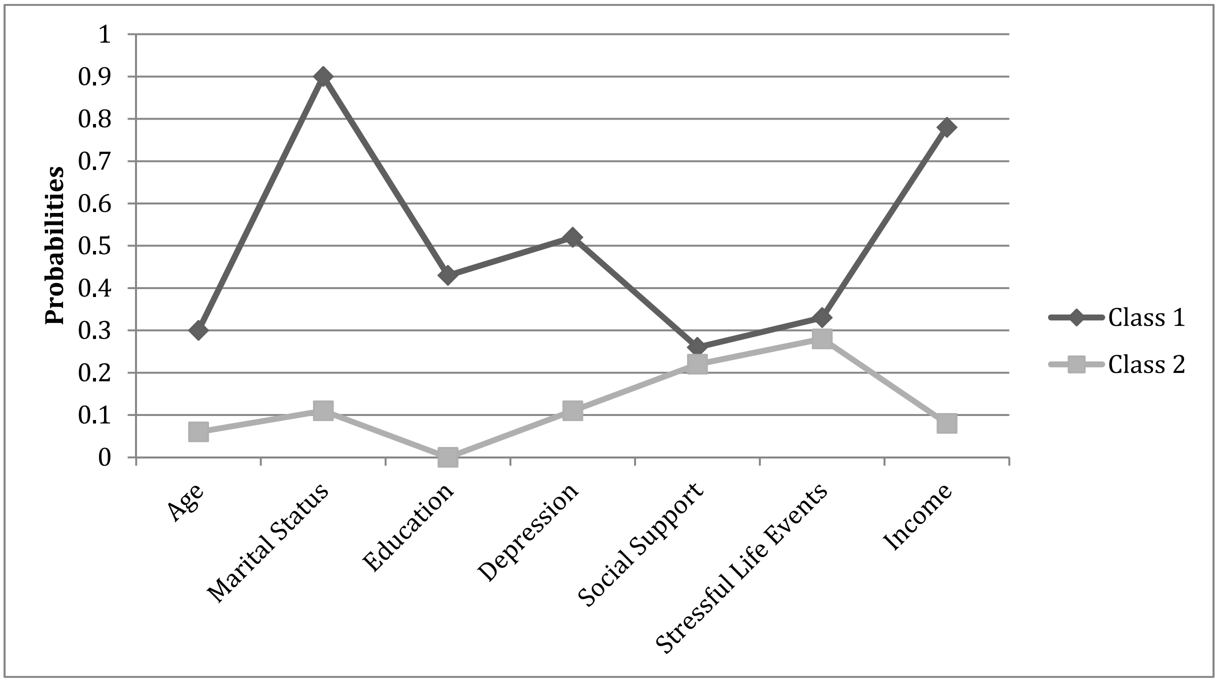
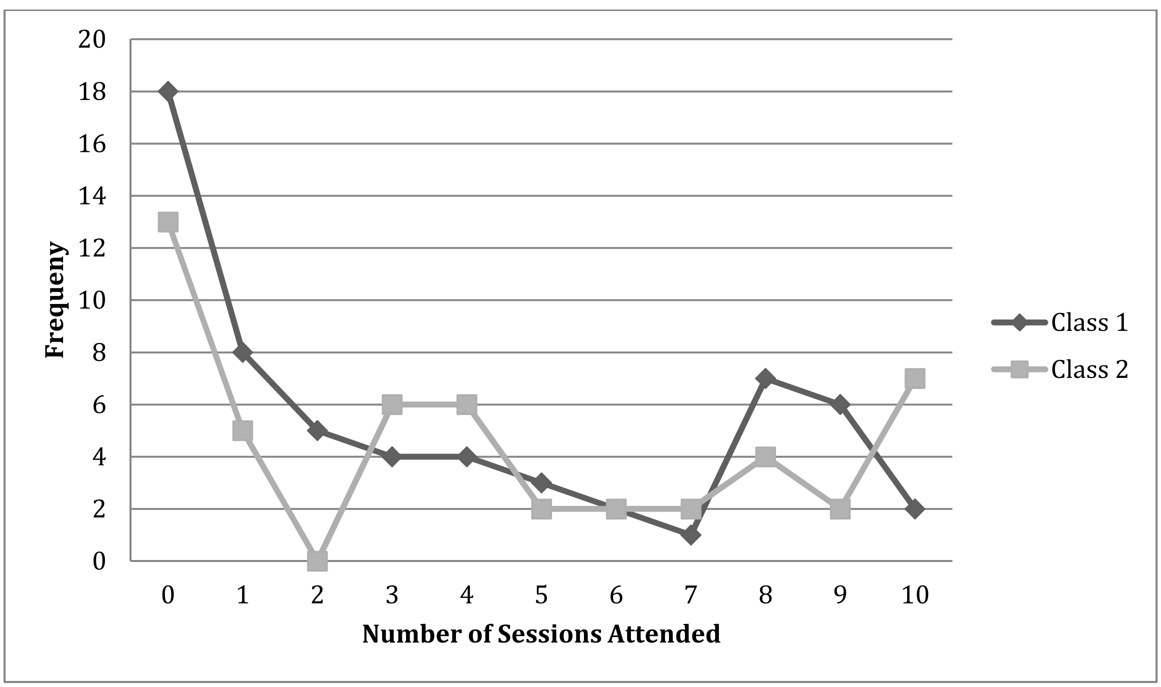


Figure 3

Distribution of Sessions Attended, Separated by Class Membership for the 2-Class Model



3-class model. Class 1 was the most common class (*n*=48), and had the lowest overall levels of risk factors, as well as the highest mean number of parent training sessions attended (*M*=4.23, *SD*=3.67). This class was most distinctively classified by income and marital status; the majority of the participants in this class had a parenting partner and all had an income above the poverty line.

Class 2 was almost as common as class 1 (*n*=44), but this class had the lowest mean number of parent training sessions attended (*M*=3.114, *SD*=3.34), as well as higher overall levels of risk factors. This class was characterized predominantly by education and caregiver depression; all the caregivers who did not complete high school were in this class, and this class had the highest mean score on the BDI.

Class 3 had the fewest number of participants (*n*=18), and was characterized by moderate to low levels of most risk factors. Class 3 has a profile similar to class 1 in many respects; however, it differs in regards to income and marital status. Most of the participants in class 3 had no parenting partner and reported incomes below the poverty line. The mean attendance for this class was between class 1 and class 2 (*M*=4.06, *SD*=3.84).

See table 6 for the complete results in probability scale, and figure 4 for a graph of the probabilities of endorsement for each risk factor, broken down by most likely class membership.

A one-way ANOVA on the total number of parent training sessions attended did not reveal a main effect for class membership, F (2,107) = 1.15, p =.32. Figure 5 is the distribution of attendance for each class; like the 2-class model, the attendance distributions are similar for all three classes. This suggests that the lack of a significant F-statistic is not due to the relatively small size of the sample.

There was also no main effect for class membership on mean levels of engagement, F (2, 52) = 1.74, p=.19. Class 3 had the highest mean engagement (*M*=3.73, *SD*=.69), followed by class 2 (*M*=3.73, *SD*=1.00), and class 1 had the lowest mean engagement (*M*=3.26, *SD*=1.03).

Table 6

Probabilities of Class Membership for Each Risk Factor

Risk Factors	Class 1	Class 2	Class 3
Age at birth of target child (in years)			
19 or older	.93	.62	.99
18 or younger	.07	.38	.01
Marital Status			
Has parenting partner	**.74**	.12	.16
Does not have parenting partner	.26	.88	.84
Stressful Life Events			
2 or fewer stressful life events	.69	.64	.83
3 or more stressful life events	.30	.36	.17
Income			
Earns more than $15,000 a year	**1.00**	.24	.16
Earns less than $15,000 a year	.00	.76	.84
Education			
At least High School or GED	1.00	.44	1.00
Less than High School	.00	.57	.00
Social Supports			
3 or more social supports	.76	.69	.94
2 or fewer social supports	.24	.31	.06
Depression (BDI Score)			
BDI score ≤ 9	.87	.32	1.00
BDI score ≥ 10	.13	.68	.00

Figure 4

Probabilities of Endorsement of Each Risk Factor: 3-Class Model

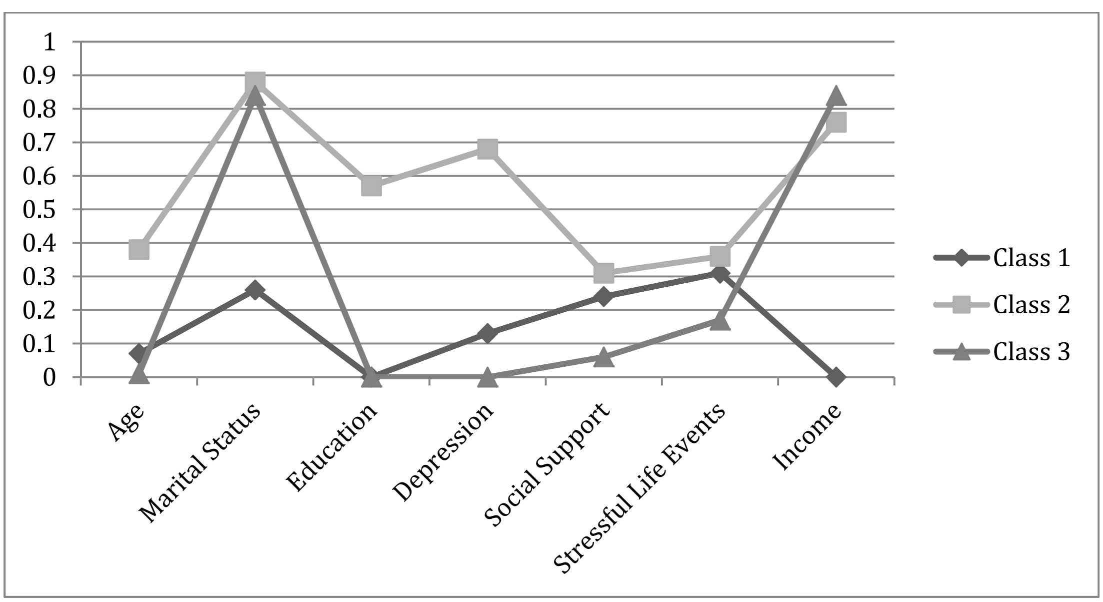
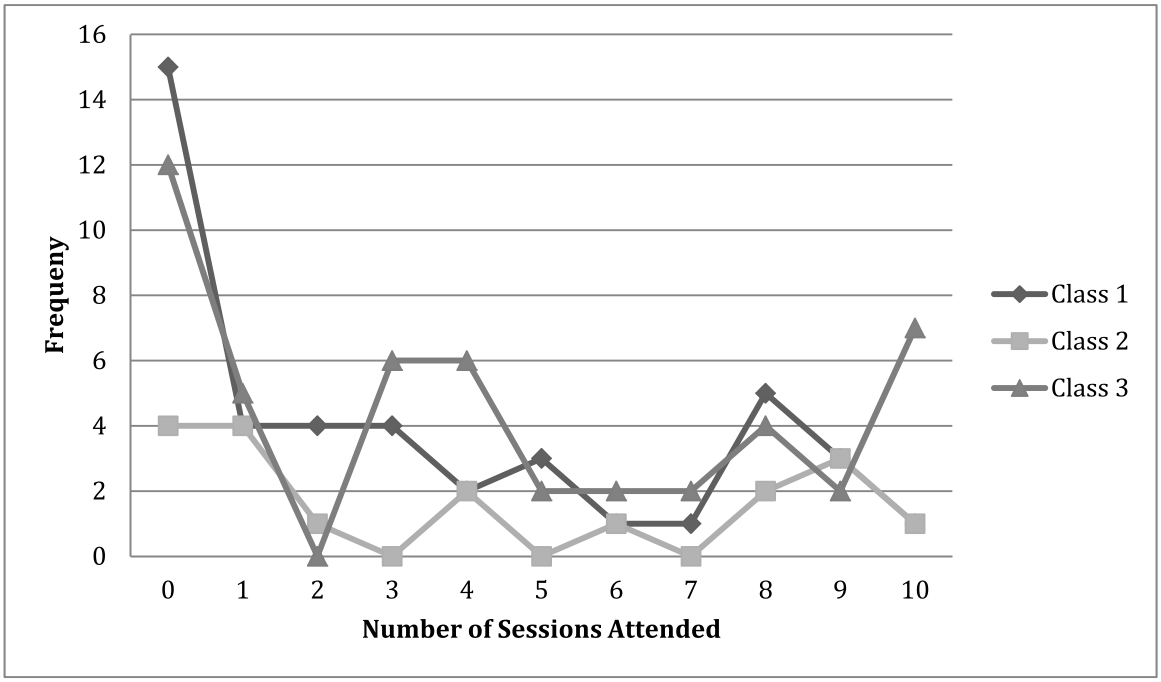


Figure 5

Distribution of Sessions Attended, Separated by Class Membership: 3-Class Model



Backward Stepwise Regression

Risk factors were entered into a backward stepwise regression, and those that made a unique contribution to prediction of attendance at parent training were retained in the final models. At each step, the variable which explained the least amount of variance was excluded. The first model included all seven predictors, the seventh mode included one predictor which explained the most variance. None of the risk factors made a unique contribution in the first five models; however, in the sixth model, social support was marginally significant (p=.10), and there was a trend for stressful life events (p=.12). For this model, R^2=.05, and F (2,103) = 2.60, p=.08. Social support and stressful life events were the only predictors in this model; all other risk factors were excluded. The seventh model included only social support and was not statistically significant; R^2=.02, and F (1,104) = 2.62, p=.11. See table 7 for a breakdown of the iterations and sequencing of variable exclusion.

Table 7

Backward Stepwise Regression

Model		*b*	*SE b*	Beta	*p*	R^2	*F*
1						.07	1.03
	(Constant)	2.28	2.21		.30		
	Age	.04	.06	.06	.58		
	Marital Status	-.08	.88	-.01	.93		
	Income	.16	.15	.14	.26		
	Education	-.12	.41	-.03	.78		
	Depression	.02	.05	.04	.74		
	Social Support	.19	.13	.15	.15		
	Stressful Life Events	-.27	.20	-.14	.16		
2						.07	1.21
	(Constant)	2.30	2.20		.30		
	Age	.04	.06	.06	.57		
	Income	.16	.13	.14	.22		
	Education	-.12	.40	-.03	.76		
	Depression	.02	.05	.04	.73		
	Social Support	.19	.13	.15	.14		
	Stressful Life Events	-.28	.19	-.14	.16		
3						.07	1.45
	(Constant)	1.90	1.75		.28		
	Age	.03	.06	.06	.59		
	Income	.14	.12	.13	.23		
	Depression	.02	.05	.04	.69		
	Social Support	.19	.13	.14	.15		
	Stressful Life Events	-.28	.19	-.14	.15		
4						.07	1.79
	(Constant)	2.18	1.6		.17		
	Age	.03	.06	.05	.63		
	Income	.13	.12	.12	.26		
	Social Support	.19	.13	.14	.15		
	Stressful Life Events	-.26	.19	-.14	.17		
5						.06	2.32†
	(Constant)	2.83	.85		.001		
	Income	.15	.11	.13	.19		
	Social Support	.19	.13	.14	.15		
	Stressful Life Events	-.27	.19	-.14	.15		
6						.05	2.59†
	(Constant)	3.35	.76		.00		
	Social Support	.21	.13	.16	.10		
	Stressful Life Events	-.30	.19	-.15	.12		
						.07	2.62
7	(Constant)	2.81	.68		.00		
	Social Support	.21	.18	.16	.11		

Notes: $R^2\Delta$ = .00 for Model 2; $R^2\Delta$ = -.001 for Model 3; $R^2\Delta$ = -.001 for Model 4; $R^2\Delta$ = -.002 for Model 5; $R^2\Delta$ =- .02 for Model 6; $R^2\Delta$ =- .02 for Model 7. *†p*<.10.

Binary Segmentation Procedure: SEARCH

All seven risk factors were entered into MicrOsiris's SEARCH program, and attendance at parent training was set as the dependent variable. The split criteria used was a maximum reduction in error variance. The stop criterion, for no further splits, was when there were either no additional splits that significantly reduced the error variance relative to the starting error, or if an additional split would result in fewer than ten participants in a terminal node. The stability and predictive validity of the model drops when there is a small *n* in the terminal nodes, and the generalizability of the findings is compromised. The final model had four splits, and five mutually exclusive subgroups; see figure 6 for the classification tree. Only two of the seven predictors entered into SEARCH were used in the final model; social support and stressful life events were each used twice.

A one-way ANOVA on the total number of parent training sessions attended revealed a significant main effect for group membership, F (4, 105) = 2.81, p =.03. Post hoc comparisons using Fisher's LSD procedure indicated that participants classified in group 2 (M=5.24, SD=3.67) attended significantly more parent training sessions than participants in group 6 (M=2.45, SD=3.09), p<.01, and group 9 (M=2.19, SD=3.02), p<.01. See table 8 for all means, standard deviations, and mean differences using Fisher's LSD.

Table 8

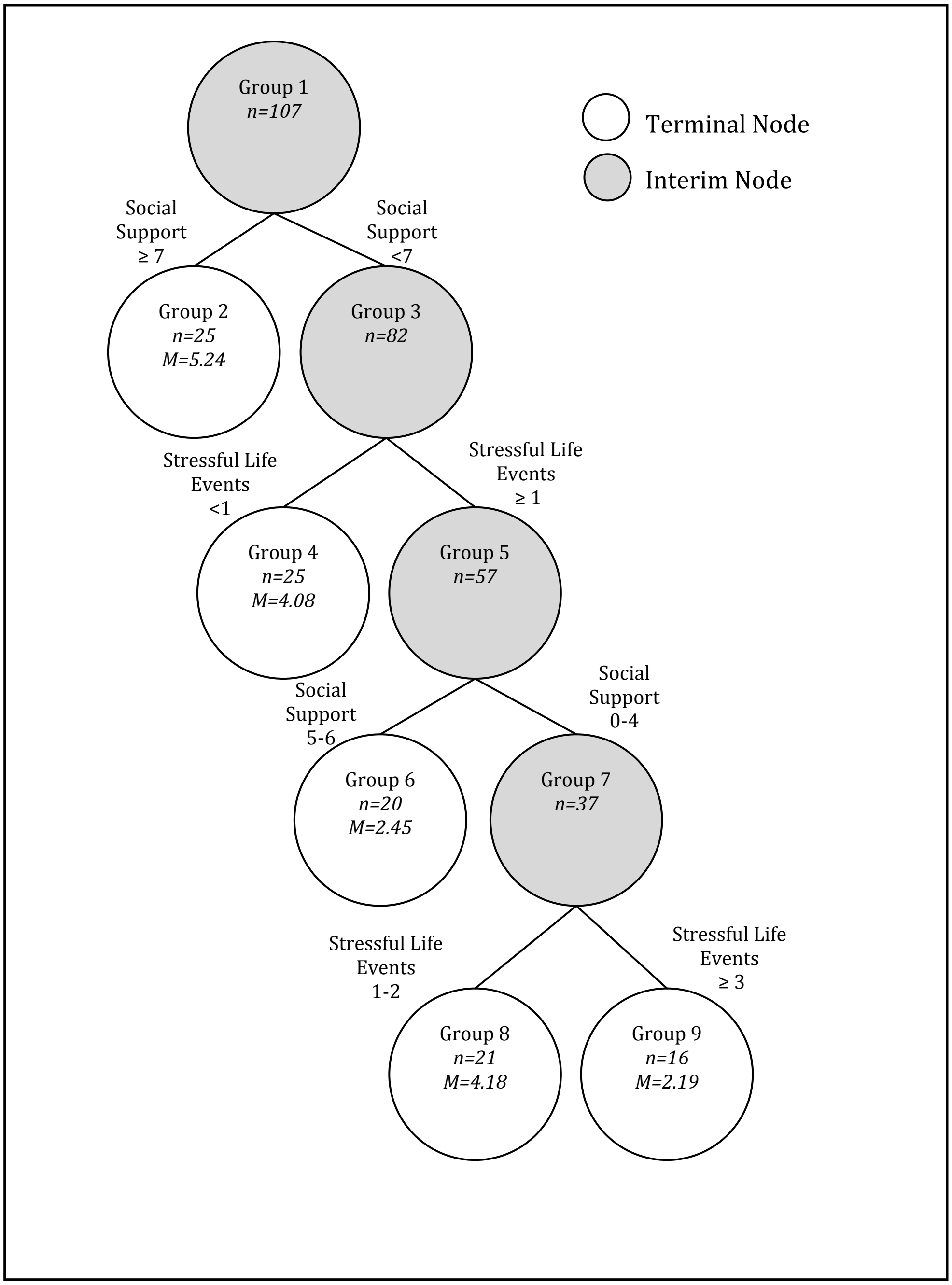
SEARCH Groups: Means, Standard Deviations and Mean Differences

Group	Attendance		Social Support		Stressful Life Events		Fisher's LSD Test of Mean Differences			
	M	*SD*	*M*	*SD*	*M*	*SD*	Vs. Group 4	Vs. Group 6	Vs. Group 8	Vs. Group 9
Group 2	5.24	3.67	8.52	1.25	2.19	1.59	1.16	2.79**	1.06	3.05**
Group 4	4.08	3.86	3.33	1.63	0	0		1.63	-.10	1.89†
Group 6	2.45	3.09	5.32	.48	2.45	1.47			-1.73	.26
Group 8	4.18	3.38	2.50	1.11	1.50	.51				1.99†
Group 9	2.19	3.02	2.19	1.22	4.38	1.82				

*Notes: **p<.01, †p<.10*

Figure 6

SEARCH Classification Tree



Notes: Figure means are the mean number of parent training sessions attended for each terminal node.

Mean attendance generally decreased for groups further from the top of the classification tree, as these groups had increasingly higher levels of the risk factors; however, this was not true for groups 6 and 8. The participants in group 6 had higher social support than the participants in group 8, and participants in both groups experienced at least one stressful life event. However, group 6 had the second lowest mean attendance, while group 8 had the second highest mean attendance; on average, participants in group 8 attended roughly two more parent training sessions than group 6. Group 6 can be labeled as the "Some stressful life events and moderate social support" Group, because these participants had experienced some stressful life events (2-3) and had moderate social support. Group 8 was the "Few stressful life events and low social support" Group because these participants experienced fewer stressful life events, but also had low social support. In short, although both groups experienced some stressful life events, the "Some stressful life events and moderate social support" participants attended fewer parent training sessions than those in the "Few stressful life events and low social support" group, despite the latter group having lower social support.

Group 2 had the highest mean attendance and was the "High social support" group. Participants in this group had very high social support relative to the rest of the sample and listed at least seven social supports. This group attended significantly more than Group 6, the "Some stressful life events and moderate social support" group. Group 2, "High social support," also attended significantly more parent training sessions than did participants in Group 9. Group 9 can be labeled as the "Many stressful life events and low social support" group because participants in this group had at least three stressful life events, and an average of 2.19 social supports.

DISCUSSION

One of the most pervasive difficulties in the implementation of preventative interventions for caregivers of children with behavior problems is the caregivers' often limited attendance at sessions. Research indicates that the dosage of intervention received affects outcome, and that the families who drop out are often the most severely impaired (Kazdin, et al., 1994; Lochman, et al., 2006). The goal of this study was to model the relationships between factors believed to contribute to low attendance at parent training sessions.

The latent class analysis revealed a 2-class model best fit the data; however, there were no significant differences in engagement or attendance between the classes. A post hoc backward stepwise regression indicated that, for this sample, social support and stressful life events accounted for the most variance in attendance. An exploratory binary segmentation procedure (SEARCH) provided additional support for the importance of these two risk factors; the SEARCH analysis split the sample into six mutually exclusive groups based on participants' level of social support and number of stressful life events. There were significant differences between these groups on number of sessions attended.

This study was designed to address two primary research questions: Are there meaningfully configurations of risk factors which identify distinct subgroups within the sample, and how are these configurations of risk factors related to treatment engagement?

Configurations of Risk Factors

The present study addressed gaps in the previous literature by using person-centered analyses, as opposed to traditional variable-centered approaches. The value of person-centered analyses for the study of engagement in prevention programs is these approaches allow for heterogeneity within the sample, and the study of individual differences in the patterning of risk factors.

The analyses indicated that there are meaningful configurations of risk factors which can be used to discriminate distinct subgroups within the sample, and there were significant differences between these subgroups on the number of parent training sessions attended. Participants were classified into these groups based on the number of the stressful life events they'd experienced in the previous year, and their level of social support. These risk factors were each used twice to successively refine the model using a binary segmentation procedure, SEARCH. The group with the highest mean attendance had the highest social support, while the group with the lowest mean attendance had lowest social support, and the greatest number of stressful life events. High social support is important for treatment engagement and increasing social support for previously isolated parents has been shown to improve child outcomes (The Conduct Problems Prevention Research Group, 2002). However, the present study hypothesized that very high social support could reduce motivation to attend group parent training and these results provide some support for this.

The mean attendance was typically highest for the groups at the top of the classification tree and decreased with subsequent splits. The first group identified (Group 2) was the "High social support" group, and this group had the highest mean attendance. The final group identified (Group 9) had the lowest mean attendance, and was the "Many stressful life events and low social support" group. Notably, two groups did not follow this general pattern. The participants in group 6 who were the "Some stressful life events and moderate social support" group, attended roughly half of the parent training sessions as the parents in the "Few stressful life events and low social support" group (Group 8). Both of these groups experienced some stressful life events; however, the participants with moderate social support (Group 6) attended fewer parent training sessions than the parents with lower social support (Group 8).

This study did not explicitly examine the mechanisms that account for the effects of these two factors. However, it may be that moderate to high social support actually serves to lessen a parent's motivation to attend group-based parent training, as was proposed by this study, but this cannot be confirmed without further research. However, this interpretation is consistent with some existing research which has shown that parents with low social support benefit more from group-based parenting intervention, relative to parents with higher social support (The Conduct Problems Prevention Research Group, 2002). Also, the sample size was insufficient to test whether the type of stressful life event better predicts attendance at parent training than the number of events.

This combination of stressful life events and low social support likely creates a challenging environment for caregivers and families. Caregivers with low social support may feel overwhelmed by daily tasks, such as laundry or grocery shopping, and may not have the personal resources to engage in parent training. Families experiencing stressful life events may also have a higher degree of familial conflict as the result of the on-going heightened stress, which could negatively impact their ability or desire to participate in prevention programs. Under these conditions, parents may feel as if they are constantly "putting out fires," and so participation in a prevention program is a low priority.

The results of the SEARCH technique are intriguing because the most commonly discussed risk factors in the prior literature, such as income and education, did not discriminate between participants on attendance or engagement variables (Kazdin, 1996). This will be discussed in greater detail in a subsequent section. Confidence in the validity of the risk factors used in the classification is bolstered by the fact that these same risk factors were retained in the final model of the backward stepwise regression.

SEARCH is a not a new methodology, and has been used in other social science disciplines, but to the researcher's knowledge, this is the first application of SEARCH to intervention research. SEARCH, and other binary segmentation procedures have been used widely since the 1960's in marketing and media-related fields to predict consumer behavior, and SEARCH has been used to predict family planning and criminological behavior (Farrington & Tarling, 1985; Robinson & Levy, 1996; Ross & Bang, 1966a, 1966b). The utility of SEARCH for intervention research is that it enables the researcher to develop data-driven hypothetical models of risk or protective factors for engagement which are then able to be tested on novel populations. Possibly the most significant advantage of SEARCH is that the classification trees are unambiguous. The "rules" for group membership are clearly specified, and ideally that group membership maps onto a particular behavior or level of risk. This may be why binary segmentation procedures haven't been applied to intervention and engagement research previously, because engagement operates on a continuum, which could make SEARCH results less clear. However, in the present study, SEARCH was able to classify the sample into groups which significantly differed on attendance, which the LCA did not, suggesting that this approach has utility for future research in engagement.

Impact of Methodology on Outcomes

As noted above, the LCA result did not converge with the results from the SEARCH and backward stepwise regression. The two classes of the LCA model which best fit the data were not significantly different in the number of parent training sessions attended, or mean level of engagement. There are several possible explanations for why the LCA and SEARCH results were discrepant. First, the LCA method uses all predictor variables to generate the models, unlike SEARCH, which only uses the predictor variables which most improve the model fit. Given that SEARCH only used two of the entered predictors, the others may have resulted in additional "noise" or error variance.

Although both SEARCH and LCA are person-centered approaches to analysis, the LCA uses only the predictor variables to classify the participants based upon patterns of responses to the predictor variables. Subsequent analyses are then used to determine if these classifications are meaningfully associated with the outcome variable, in this case attendance. SEARCH works in a nearly-reverse fashion by considering the outcome variable first and attempting to find the risk factors which discriminate best on the outcome variable.

There were three SES-related predictors which were all significantly positively inter-correlated: maternal age at the birth of the target child, income, and caregiver level of education. These predictors were also significantly negatively correlated with depression. Depression was significantly lower in married or cohabitating participants, and participants with a parenting partner also had significantly higher income and education than single parents.

By looking at the response probabilities for each model (table 5 and table 6), it is apparent that the probabilities of class membership based on marital status and income are highly discrepant between classes. So, knowing a participant's response to these items enables the prediction of class membership with reasonable accuracy. This indicates that the latent variable created by these analyses is not independent of these two observed variables, marital status and income. This lack of independence is the result of the existing relationships between the observed variables which supports the model adequately fits the data, and is not simply the result of error. However, because responses to the other items (social support, stressful life events, education, depression, and maternal age) are more evenly distributed across the classes, the model is not representing complete distinct patterns of responses.

The 2-class and 3-class LCA models that are described are reflecting response patterns related to demographic variables and not social support or stressful life events. The LCA was not able to fit a model to both the demographic variables and the remaining variables because the response probabilities of social support and stressful life events are not conditional on demographics. In other words, it is not possible to predict a participant's level of social support or frequency of stressful life events based on their demographic characteristics, so the LCA fits the model to the items with the most consistent conditional responses.

Additionally, both SEARCH and backward stepwise regression are designed for use with interval or scaled data, such as the raw data in the present study, while LCA requires the predictor variables to be dichotomized. Each of the two significant predictors in the SEARCH classification was used twice, and the initial splits did not map onto the binary splits used in the LCA. While LCA has significant utility, it may not be sensitive enough for predicting behaviors like treatment engagement because of the detail lost by dichotomizing the data.

Implications

Possibly the most surprising finding in this study was the *absence* of all the "usual suspects." Socioeconomic variables (income and education) did not significantly predict attendance, or mean level of engagement. Socioeconomic status is the most common significant predictor of engagement and attendance in the child treatment literature; however, the sample used in the present study was *not* a clinic-referred, treatment-seeking sample (Kazdin, et al., 1994). The participants in this targeted prevention study were recruited using teacher ratings of child impairment; in some cases the caregivers may not have perceived a need for the intervention.

The results of this study suggest that generalizing about the risk factors for low engagement from treatment to prevention programs may not be valid. At a fundamental level, prevention is different from mental health treatment, although the interventions may be similar. For example, the content of the Coping Power parent component used in the present study is very similar to evidence-based parent training programs used in clinical practice for the treatment of childhood externalizing disorders, such as Attention-Deficit/Hyperactivity Disorder, Conduct Disorder, and Oppositional Defiant Disorder (Chorpita & Daleiden, 2009). However, although the programs share a great deal of content, there are key differences in program implementation, target client populations, and goals for client outcomes. Except in cases where treatment services are court-mandated, child mental health treatment typically begins when the child's parent or guardian initiates it. For this to happen, the caregiver must perceive the need for treatment services, be sufficiently motivated to seek services out, and have the personal and financial resources to participate in treatment. Personal resources include time, mental capacity, organization skills, and some level of emotional stability. Without these, the parent's ability to comply with treatment recommendations is likely limited. These same personal resources are required for parents to participate in a prevention program; however, these parents are not initiating the contact with the service provider. This may be because the parent has limited financial resources, and traditional mental health services are not an option, or it the parent may not perceive a need for treatment services.

Research on mental health service usage found that parents and caregivers experiencing moderate amounts of additional strain as a result of their children's problems are more compliant with treatment services, even when the services were mandated by an outside agency, such as the juvenile court system or because of concerns about parental competency (Garland, Aarons, Brown, Wood, & Hough, 2003). This experience of strain and the caregivers' perception of how their children's problems impact the family are fundamentally different for families participating in prevention programs, rather than treatment. Another study of the Coping Power program using a different, but demographically similar, sample found that participating parents reported low levels of strain as a result of their children's problems, compared to parents in clinic-referred samples (Minney & Lochman, 2010, October). This research supports the assertion that families participating in prevention programs differ fundamentally from treatment seeking families. These parents may not perceive their children's behavior to be problematic, and in some cases, the children may not have behavior problems that are readily apparent to their parents. However, these children are still at risk for later conduct problems, and can benefit from engagement in prevention programs. Conduct problem prevention programs, like Coping Power, work—there is abundant research supporting the effectiveness of conduct problem prevention programs (McMahon, Wells, & Kotler, 2006). Furthermore, prevention programs are more cost-effective in the long run than later treatment (Foster, 2010). Left unchecked, conduct problems are costly and negatively impact the lives of the children, their families, and their communities (Jones & Foster, 2009). Clearly, it is worth investing in prevention, but the issue remains of how to get parents to engage in prevention programs. This study provides further evidence that prevention is NOT treatment, and the reasons families don't participate are different. Families do not fail to engage in prevention programs because they can't afford to, they fail to engage because they don't have the personal resources. They lack time, or social support, or they have too many other stressors and their child's behavior isn't causing as much stress as the new baby at home, or the new job.

Successfully engaging parents in prevention programs like Coping Power will require service providers to change their mindset about why parents don't engage, and develop innovative strategies to increase engagement that focus on the personal reasons parents fail to engage, rather than attempting to generalize and adapt strategies used in the clinical treatment literature.

Potential Limitations

Several limitations of the study and the analyses used are worth noting. Both LCA and SEARCH are typically used with samples of 1000 or more participants, and the sample used in the present study was just over a hundred participants because of missing data. This may have inhibited the ability of the LCA to generate a stable model and limits the overall generalizability of the results. Ideally, when using SEARCH, the model is developed using one sample, and then confirmed on a novel sample. The present study did not have sufficient participants available to do this type of confirmatory analysis of the model.

Both the LCA and SEARCH models are derived from the predictors entered into the analyses, and the resulting models are a function of which predictors were included and excluded. Child level predictors were not entered into the analyses, such as parent and teacher reported level of behavior problems, which may have impacted the results.

Additionally, these results may have been different from existing research because of the sample. The sample used in the present study had a high percentage of single parents, and many participants were low socio-economic status. However, this is characteristic of many parents who are targeted for participation in similar interventions, and these results may reflect true differences.

A final potential limitation is measure of social support that was used. Caregivers listed their social supports and rated their satisfaction with each person they listed. Most caregivers rated every person at the highest point on the scale which suggests participants only listed individuals whom provide strong social support. Future research could consider alternative methods of measuring social support to avoid this ceiling effect.

Future directions

Future research should consider other parent and child factors which may be related to attendance and engagement in targeted prevention parenting programs.

One potential moderator could be the level of caregiver strain experienced by the primary caregivers; caregiver strain in this context is conceptualized as the additional burden experienced by a caregiver as a result of the child's problems (Ana Maria Brannan, Heflinger, & Bickman, 1997). Caregiver strain includes both subjective burden, such as worry about the child or guilt over the child's problems, and objective burden, such as loss of personal time or lost wages from missing work (Bickman, et al., 2007). A moderate level of caregiver strain has been associated with more consistent parental engagement in treatment for their child's problems, as well as more intensive services received, and fewer gaps in care; caregiver strain is a robust predictor of which children get mental health services, even when controlling for baseline severity of symptoms (Ana Maria Brannan & Heflinger, 2006; Ana Maria Brannan, et al., 1997; Ana María Brannan, et al., 2003; Garland, et al., 2003; Garland, et al., 2005).

Recent data from a different sample of caregivers of children recruited for the Coping Power program found that that these caregivers have lower reported levels of caregiver strain than do clinic-referred caregivers (Minney & Lochman, 2010). This suggests these caregivers do not perceive their children to have problems and may not be able to be motivated or engaged through the same mechanisms as caregivers who bring their children in for treatment.

Additionally, future research could focus on which specific types of stressful life events may have a greater impact on attendance. Having a baby or moving to a new neighborhood may impact a caregiver's attendance at parent training more, or less, than a death in the family or legal difficulties.

Another consideration for future research is whether these risk factors operate in the same way when structure of the intervention delivery is different. The results of this study indicating parents with low social support engage more in prevention programs is consistent with existing literature, but low social support may not provide motivation to engage if the intervention is delivered in an individual, rather than group format (The Conduct Problems Prevention Research Group, 2002).

Finally, future research should characterize engagement more broadly and use a variety of measures to capture caregivers' engagement and investment in parent training, rather than relying on attendance. The dosage of treatment is important for outcome, but the caregivers' engagement in session and comprehension of skills and concepts is equally important for implementation.

EXOSYSTEM SOCIAL SUPPORT

1. Who do you know that you can count on for help or support when you need it, or when you are feeling down in the dumps, or are upset about something?
(**INTERVIEWER**: *The participant may name up to 10 people. Fill in the response in Column 1 and Column 2. Place the corresponding number from the list below in Column 3*)

1=MOM	2=DAD	3=GRANDMOTHER
4=GRANDFATHER	5=SIBLING	6=AUNT
7=UNCLE	8=SON	9=DAUGHTER
10=COUSIN	11=NEICE	12=NEPHEW
13=FRIEND	14=PREACHER	15=COWORKER
16=COMMUNITY AGENCY WORKER		17=OTHER/EXHUSBAND
18=SPOUSE	19=FAMILY	20=SIG. OTHER

INTERVIEWER: "For questions 2 and 3, please use the following scale to rate how satisfied you are with the support you receive from each of the individuals you listed.

1	2	3	4	5	6
very dissatisfied	**mostly dissatisfied**	**a little dissatisfied**	**a little satisfied**	**mostly satisfied**	**very satisfied**

2. How satisfied are you with the help and support you receive from the people you listed? (**INTERVIEWER**: *Circle response in Column 4*)

3. How satisfied are you with the support you receive from these individuals about issues involving your child? (**INTERVIEWER**: *Circle response in Column 5*)

Initials	Relationship	Code	Question 2	Question 3
EX: M.B.	FRIEND	13	1 2 3 4 5 6	1 2 3 4 5 6
1.			1 2 3 4 5 6	1 2 3 4 5 6
2.			1 2 3 4 5 6	1 2 3 4 5 6
3.			1 2 3 4 5 6	1 2 3 4 5 6
4.			1 2 3 4 5 6	1 2 3 4 5 6
5.			1 2 3 4 5 6	1 2 3 4 5 6
6.			1 2 3 4 5 6	1 2 3 4 5 6
7.			1 2 3 4 5 6	1 2 3 4 5 6
8.			1 2 3 4 5 6	1 2 3 4 5 6
9.			1 2 3 4 5 6	1 2 3 4 5 6
10.			1 2 3 4 5 6	1 2 3 4 5 6

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