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TITLE:

Identifying treatment moderators of a trauma-informed parenting intervention with children in foster care: Using model-based recursive partitioning

AUTHORS:

Gerard Chung Siew Keong¹, David Ansong¹, Kanisha C. Brevard¹, Chen Ding-Geng¹

¹ School of Social Work, University of North Carolina at Chapel Hill

Corresponding Author:

Gerard Chung Siew Keong, <https://orcid.org/0000-0002-7852-1848>

Correspondence regarding this article should be address to Gerard Chung Siew Keong, School of Social Work, University of North Carolina at Chapel Hill, Tate-Turner-Kuralt Building

325 Pittsboro Street CB# 3550, Chapel Hill, NC 27599-3550. Email: gcsk1982@live.unc.edu

Abstract

Background: Trauma-informed parenting interventions have been used in child welfare to help caregivers respond to children in trauma-informed ways that can mitigate the effects of maltreatment and build strong caregiver-child relationships. Existing studies support its effectiveness with the foster care population. However, to further advance its development, one key step is to identify subgroups of participants that respond differently from the intervention.

Objective: To identify pre-treatment moderators that can distinguish subgroups of caregivers and children that benefit differently from the intervention. **Participants and setting:** 414 foster care children (age 3 or younger) and their caregivers were assigned either to the trauma-informed parenting intervention in the Illinois Birth through Three Title IV-E waiver demonstration or to a comparison group that received services as usual. **Methods:** Model-based Recursive Partitioning (MOB) was used to identify treatment moderators and moderator interactions. MOB fits a parametric model and uses a data-driven method to find subgroups for which the specified parametric model has different parameters. Two parametric models (logistic and linear regression) were used in accordance with two outcomes: reunification (binary), and caregiver-child attachment (continuous). We examined 21 potential pre-treatment moderators in both models. **Results:** For reunification outcome, three treatment moderators interact to produce different subgroups of participants who responded differently to the intervention: (a) caregivers' relationship status (kin vs. non-kin/permanent caregivers), (b) caregiver-child attachment, and (c) case history of physical abuse. For attachment outcome, caregivers' age was found to be a treatment moderator. Future developments of trauma-informed interventions should consider these moderators.

Key words: trauma; parenting; foster children; model-based recursive partitioning; moderators; reunification

Introduction

Each year in the United States, a large number of children are removed from their parents' custody and placed in the protective custody of child welfare authorities, typically resulting in foster care placements. According to the U.S. Department of Health and Human Services (2018), from 2013 to 2017 the number of children annually entering foster care increased 6% from 254,622 to 269,690. A large percentage of children in foster care are also under the age of four (36% in 2016; U.S. Department of Health and Human Services, 2018) – a concerning statistic in light of evidence that children who experience traumatic events (e.g., maltreatment) at a young age are at greater risk for later emotional and behavioral disorders and impairments across multiple domains of development (Cook et al., 2005). Trauma-informed parenting interventions have been developed to help treat these symptoms of trauma exhibited by children, and several studies have supported their effectiveness including among children in foster care settings (Fraser et al., 2013; Lindstrom et al., 2018; Murray et al., 2019; Sullivan et al., 2016). However, to advance the development of trauma-informed parenting interventions for the foster care population, studies must move beyond the question of whether an intervention works in general to assessing which subpopulations an intervention works for within the foster care population (Kraemer et al., 2006). To this end, the present study aims to identify treatment moderators that can distinguish subgroups of children and their caregivers that benefit differently from trauma-informed interventions.

Trauma-Informed Parenting Interventions

Child welfare services are increasingly employing trauma-informed parenting interventions because they address the detrimental effects of maltreatment on children's mental and physical wellbeing (Lindstrom et al., 2018; Murray et al., 2019). Research has shown that

consistent and responsive parenting can mitigate the adverse consequences of child maltreatment and promote healthy attachments between children and caregivers (Fraser et al., 2013). For instance, a meta-analysis (Lindstrom et al., 2018) found that trauma-informed parenting interventions for parents and caregivers of children exposed to different types of violence (including child maltreatment) had moderate to large effects on parenting and child outcomes, including positive parenting practices and improvements in children's internalizing and externalizing problems, and trauma symptoms. Therefore, trauma-informed parenting interventions designed to help parents, adoptive parents, or foster parents respond to children in trauma-informed ways can help mitigate the traumatic effects of maltreatment on children and foster strong relationships with their children.

Benefits of Understanding Differential Effectiveness of Interventions in Child Welfare

Another key finding of Lindstrom and colleagues' (2018) meta-analysis was that the effectiveness of these interventions varied considerably among these studies' participants. Notably, they found that these variations were associated with pre-treatment factors related to the families', individuals', and cases' circumstances, such as sociodemographic factors and the types of violence exposure (e.g., intimate partner violence, child maltreatment, or community violence). Understanding the key factors behind this differential effectiveness may help inform future intervention development. However, most trials of trauma-informed parenting interventions to date have focused on estimating the intervention's average treatment effects across individuals in the treatment group, even though this average treatment effect may not apply to individuals or subgroups (e.g., males versus females) within the treatment (Kraemer et al., 2002, 2006). Yet trials are not only useful for testing questions about effectiveness. They are

also important for understanding which individuals benefit from the intervention before an intervention is implemented widely (Gardner et al., 2010).

In the child welfare system, practitioners face the challenge of determining the most appropriate evidence-based parenting intervention for each family they serve (Horwitz et al., 2010). Understanding what works and for whom can help practitioners better meet the specific needs of each family. In 2014, a workgroup convened by the Children's Bureau of the Administration for Children and Families and the U.S. Department of Health and Human Service created the Framework to Design, Test, Spread, and Sustain Effective Practice in Child Welfare (Framework Workgroup, 2014). This framework laid out a series of steps to follow in order to develop and implement effective interventions in the child welfare sector. Notably, the stage following intervention development and testing is the "Compare and Learn" stage. This stage requires researchers and practitioners to identify for whom the intervention was most and least effective and under what conditions. The exploration of treatment moderators is one method that can identify factors associated with any differences in an intervention's effects.

Treatment Moderators in Trauma-Informed Parenting Interventions

Treatment moderators are baseline or pre-treatment variables that have an interactive effect with treatment on treatment outcomes, such that the magnitude or direction of the effect differs across interventions (e.g., women respond better to treatment X, whereas men respond better to treatment Y). Predictor variables differ from moderator variables in that the association of the predictor variable with treatment outcome does not differ across treatments (Kraemer et al., 2002). Moderators may be assessed for when evidence of a strong treatment effect exists but also when the average effectiveness of an intervention is weak, potentially indicating that the intervention is effective only for a subset of the treatment group (Frazier et al., 2004).

To inform our choice of treatment moderators for the present study, we examined 21 studies included in a meta-analysis of trauma-informed parenting treatments for children exposed to violence, including child abuse (Lindstrom et al., 2018). Of these 21 studies, we found only five studies that examined treatment moderators. Ashton and colleagues (2016) found that families of children with PTSD who started the treatment with poorer scores in the Parenting Relationship questionnaire improved more on the parenting relationship outcome at the end of the treatment. Cohen and his team's (2004) study of children with abuse-related PTSD symptoms hypothesized several child-level factors (gender, age, and ethnicity/race) as treatment moderators, but they did not find evidence to support their hypotheses. Similarly, Deblinger et al.'s (2001) study did not find significant moderating effects of child age on the effectiveness of different group therapy models for children who have been sexually abused. A study by Kiser and colleagues (2015) also found that child age did not explain any variation in family functioning outcomes for their intervention for children who are experiencing PTSD. Graham-Bermann and Miller-Graff (2015) found that parents with higher levels of depression displayed poorer post-treatment positive parenting skills. Finally, Friedrich and et al. (1992) found that pre-treatment social support, maternal depression, and characteristics of the abusive incident (e.g., duration and severity of abuse) were moderators of children's externalizing and internalizing behavior in an intervention with boys. In summary, trials of trauma-informed parenting interventions to date have identified possible treatment moderators at different ecological levels of families, but evidence of these moderators remains limited and sometimes inconsistent.

Using Model-based Recursive Partitioning to Explore Treatment Moderators

A second consideration in exploring treatment moderators concerns the analytical approach used. Researchers have frequently employed a moderator analysis to answer questions

about which subgroups of caregivers and children benefit differently from an intervention, typically by adding an interactional term between the proposed treatment moderator and the treatment group into a regression model (for further explanation of this method, see Baron & Kenny, 1986; Frazier et al., 2004; Hayes, 2018; Kraemer et al., 2002). This method has also been applied to data from trauma-informed parenting interventions (Cohen et al., 2004; Kiser et al., 2015). One challenge of moderator analysis is determining which treatment moderators to include in the model given the large pool of possible moderators (Strobl et al., 2009). Limitations of using moderator analysis in a regression model or parametric framework include: (a) the low power of its results when the sample size is small (Shepherd-Banigan et al., 2020); (b) the low power of its results when there are a large number of predictors but a small sample size (i.e., a small n and large p issue; Strobl et al., 2009); (c) modeling of non-monotonic relationships between variables (Strobl et al., 2009); and (d) interpretation of complex interactions (i.e., 3-way or more; Strobl et al., 2009).

A novel method that avoids these limitations is Model-Based Recursive Partitioning (MOB; Strobl et al., 2009; Seibold et al., 2016; Zeileis et al., 2008). MOB specifies a basic parametric model to examine the relationship between the treatment group and an outcome and uses a data-driven approach to generate different parameters of this model based on treatment moderators. Advantages of MOB include its ability (a) to handle many moderator variables at once in one model; (b) to model non-linear and non-monotonic relationships; and (c) to capture higher-order interaction effects between variables. MOB also provides specific cut-off points for the moderator variables to facilitate researchers' identification of subgroups with different responses to the treatment. The results of MOB can be also be visually represented as a decision

tree, making interpretations of higher-order interactional effects (representing different subgroups) easier than in results furnished by regression models (Strobl et al., 2009).

Unlike regression models that require a prior hypothesis, MOB uses a data-driven approach to identify moderators and moderator interactions. This approach is suitable when the study goals are exploratory, when research questions seek to identify associations, and when the model will include a large number of moderators (Shepherd-Banigan et al., 2020; Strobl et al., 2009). However, unlike conventional decision trees (e.g., classification and regression tree [CART] models) which are purely data-driven, MOB also allows for the fitting of a parametric model to represent a theory-driven hypothesis (in this case, a treatment-outcome model), which is essential for social sciences research. This parametric model is then assessed using the MOB algorithm to search for treatment moderators that statistically alter the parameters of the parametric model (Kopf et al., 2010).

Studies of child welfare have employed MOB as an analytical tool to predict the odds of serious maltreatment (e.g., published in this journal is Thurston & Miyamoto, 2018). Our study sought to advance the use of MOB by demonstrating its usefulness for exploring pre-treatment moderators that identify disparate subgroups that respond differently to child welfare interventions. Specifically, we aimed to identify which subgroups of caregivers and children respond differently to a trauma-informed parenting intervention in comparison to children who receive standard foster care services. Our choice of moderators was informed by previous studies in the general parenting literature as well as studies of trauma-informed parenting interventions specifically used in the field of child welfare. By increasing our knowledge of treatment moderators in trauma-informed parenting interventions, our study represents an important step

toward the development and refinement of interventions outlined in the Framework to Design, Test, Spread, and Sustain Effective Practice in Child Welfare (Framework Workgroup, 2014).

Method

Description of IB3

The Illinois Birth through Three Title IV-E waiver (IB3) supported the adaptation of evidence-supported, trauma-informed parenting programs to the care and permanency planning for young children (i.e., aged 3 or younger) who were taken into the legal custody of the Illinois Department of Children and Family Services (DCFS). In IB3, two interventions – Nurturing Parenting Program (NPP) and Child-Parent Psychotherapy (CPP) – were adapted to meet the needs of children involved in the child welfare system who had experienced trauma and to help their parents or caregivers create supportive and nurturing parent-child relationships. NPP is a group intervention for caregivers that aims to enhance parenting competencies (e.g., emotional communication skills and positive parent-child interaction skills). CPP is a dyadic (i.e., caregiver and child) intervention to strengthen the caregiver-child relationship and to promote the safety and mental health of the child. A detailed discussion of the adaptation and evaluation of CPP and NPP is in Illinois DCFS (2018). Since the present study is focusing on IB3’s overall goals, we will not focus on the treatment effects of the individual programs.

The outcome evaluation of IB3 found that children allocated to the intervention group had a higher likelihood of family unification (i.e., reunifications and legal guardianships with biological and fictive kin) than did children assigned to services as usual (comparison group; Illinois DCFS, 2018). However, the study found no statistically significant differences between children in the intervention and comparison groups with respect to standardized assessments of caregiver-child attachment quality. However, the report identified different pathways to

permanence based on several demographic variables. For instance, older children were more likely to return home, and younger children were more likely to become adopted by foster or kin caregivers. Thus, it was necessary to explore treatment moderators that could explain differences in outcomes across subgroups.

Data and Sample

Between July 1, 2013, and June 30, 2017, 1,889 children in Cook County, Illinois, were assigned to the IB3 waiver demonstration, accounting for 21% of all age-eligible children entering legal custody in Illinois during this observation period. Children were assigned to the intervention or comparison groups based on the DCFS's existing rotational assignment procedure, which ensures that every agency receives a fair mixture of cases with similar case complexity. Using a two-tiered unbiased allocation procedure to assign cases, DCFS offices and voluntary agencies were randomized by DCFS to treatment or comparison clusters, and child cases were rotationally assigned to intervention and comparison agencies. In principle, this procedure ensured that systematic differences between the two groups would only occur by chance (see detailed discussion in Illinois DCFS, 2018). Caregivers of children who entered foster care during state fiscal years 2014 and 2015 were recruited to complete caregiver surveys ($N = 1029$). These caregivers were selected because at least two years had passed since their children had entered the system, and because they would be able to report on items related to permanency, child behavioral and emotional problems, and their participation in the intervention.

Our study sample first focused on 764 children and data from interviews completed by their caregivers. We then limited our sample to those children whose caregivers had completed one follow-up interview during the study period, yielding a final analytical sample of 414

children whose caregivers had completed surveys at pre-treatment and at their last follow-up point during the intervention.

Table 1 provides descriptive characteristics for the full analytical sample and for the treatment and control groups. Our analytical sample consisted of children who were mostly African American or Black (70%). Their average age was 14.13 months ($SD = 14.10$), and there were equal proportions of males and females. Caregivers of children in the analytical sample were mostly female (91%), African American (62%), had an education level above high school (58%), and had an average age of 46.33 years ($SD = 10.97$). Of these caregivers, 31% were birth or adoptive parents, 24% were kinship caregivers, and 44% were non-kin caregivers. As shown in Table 1, being in the treatment or control group was not associated with any child or caregiver pre-treatment characteristics, with the exception of caregiver education ($\chi^2[1] = 7.09, p < .01$), prior parenting services received ($\chi^2[1] = 11.94, p < .01$), and quality of neighborhood ($t[412] = -2.47, p < .05$).

Table 1 *Baseline Descriptive Statistics*[illegible]

Female	375	91%	178	89%	197	92%		
Male	39	9%	21	11%	18	8%		
Relation with Child							1.49	0.47
Permanent	130	31%	57	29%	73	34%		
Kin	101	24%	52	26%	49	23%		
Non-kin	183	44%	90	45%	93	43%		
Education level							7.09	<.01
High school and below	174	42%	97	49%	77	36%		
More than high school	240	58%	102	51%	138	64%		
Employment							0.05	0.82
Yes, currently employed	266	64%	129	65%	137	64%		
No, currently unemployed	148	36%	70	35%	78	36%		
Received parenting services							11.94	<.01
No	262	63%	109	55%	153	71%		
Yes	152	37%	90	45%	62	29%		
Emotional support (#)	5.03	1.89	4.90	1.96	5.16	1.82	-1.39	0.16
Financial support (#)	1.53	1.20	1.44	1.23	1.62	1.17	-1.54	0.12
Parenting support (#)	3.74	2.07	3.65	2.12	3.83	2.02	-0.88	0.38
Quality of social support	1.76	0.37	1.73	0.41	1.79	0.34	-1.58	0.11
Parent-child level								
AAPI	151.33	19.27	150.47	18.85	152.13	19.65	-0.88	0.38
Attachment (DECA)	46.97	10.48	46.61	10.74	47.31	10.25	-0.68	0.49
Community-level								
Neighborhood quality	1.55	0.44	1.49	0.45	1.60	0.43	-2.47	<.05

Note: emo/beh = emotional, behaviors, or learning problems;
¹n/% for categorical variables and *M/SD* for continuous variables

Measures

We focused on two outcomes in this study: (a) family reunification and (b) the attachment relationship between caregiver and the child.

Family Reunification Outcome. Family reunification, defined as a child returning home to their birth parents or to the legal guardianship of biological kin, was coded as a binary variable (0 = *no*, 1 = *yes*), with 26% of cases achieving family reunification. We collected data on case reunification from the Illinois DCFS's administrative data system. We focused on reunification because most studies to date of trauma-informed interventions have not examined case outcomes (Murray et al., 2019). Moreover, the overall goal in foster care is to return children to their own families or an alternative family. In this regard, it is paramount to identify any moderators of reunification in order to best achieve this goal in each individual case.

Attachment Relationship Outcome. We measured child-caregiver attachment at pre-treatment and then at the last follow-up during the intervention using the Devereux Early Childhood Assessment (DECA). DECA is a standardized strength-based assessment that examines protective factors and screens for social and emotional risks in young children aged 4 weeks to 36 months (Powell et al., 2007). Attachment is defined by DECA as the “mutual, strong, long-lasting relationship between the toddler/infant and significant adults such as family members” (Powell et al., 2007, p. 7), and prior research has shown that strong attachment to a caring adult is a protective factor against the effects of trauma on child development (Goldsmith et al., 2004). In this assessment, caregivers responded to statements such as “During the past four weeks, how often did the child smile back at a familiar adult?” or “During the past four weeks, how often did the child show affection for a familiar adult” on a 5-point Likert scale (0 = *never*

to 4 = *very frequently*). The items were summed up to obtain a composite score ($M = 47.48$, $SD = 9.22$).

Treatment Moderators (Pre-treatment). We used twenty-one variables proposed as treatment moderators at the child level, caregiver level, and community level (Table 1). In MOB, these moderators are tested as partitioning variables (Seibold et al., 2016) for the treatment-outcome model. Child-level treatment moderators included child race, gender, and age in months at pre-treatment. We also included a variable that indicated whether a child had any learning, behavioral, or emotional problems based on their caregiver's report. We used three items from the caseworker's assessment to assess whether the child had experienced physical abuse, neglect, or witnessed family violence at pre-treatment.

As treatment moderators, we tested data on caregivers' race, age in years, education level (i.e., high school and below vs. beyond high school), employment status, and relationship with their child (i.e., kinship, biological, or adoptive parents vs. non-kinship caregivers). We also included a measure of caregivers' parenting and rearing attitudes (e.g., expectations for the child, empathy towards the child, use of corporal punishment, and caregiver role responsibilities) based on the Adult-Adolescent Parenting Inventory (AAPI-2). The AAPI-2 has demonstrated utility in assessing potential child maltreatment in the first four years of a child's life (Kotch et al., 1999). We also included measurements of caregiver-child attachment quality at pre-treatment obtained using DECA. To provide data for three additional variables, caregivers reported the number of their emotional, financial, or parenting support sources during the 12 months before treatment. These sources could include spouses, friends, professionals, and co-workers. As a treatment moderator, we also recorded whether parents or caregivers had received any training in parenting skills prior to treatment (binary variable).

As a community-level treatment moderator, we included a variable that measured caregivers' perceived quality of their community based on various community problems: namely, whether drugs, gangs, or crime were not a problem, somewhat of a problem, or a big problem in their neighborhood.

Analytic Method

All data were analyzed in R studio version 1.2.5. Potential treatment moderators were examined using MOB (Hothorn & Zeileis, 2015) using the R “partykit” package (Zeileis & Hothorn, n.d.). MOB enables researchers to analyze interactions between treatment moderators and the treatment indicator in order to identify subgroups of participants with different responses to the treatment (Seibold et al., 2016). Studies that have used MOB to explore treatment moderators include interventions with eating disorders (Aardoom et al., 2017), caregivers' burden (Shepherd-Banigan et al., 2020), and depression (Driessen et al., 2016). In the present study, we tested 21 variables (Table 2) as treatment moderators to explore subgroups whose data demonstrated different relationships between the treatment and the outcome.

Modeling in the MOB algorithm proceeds via the following steps: (1) fit a parametric model to the dataset; (2) test for parameter stability across a set of partitioning variables (i.e., treatment moderators); (3) if there is some overall parameter instability, split the dataset for the variable associated with the highest instability; and (4) repeat the procedure in each of the resulting subgroups (Zeileis et al., 2008). Our study fitted two separate parametric models by following steps 1 through 4.

The first parametric model was a logistic regression in which reunification (binary variable) was regressed on the treatment indicator (0 = control, 1 = treatment); the second parametric model was a multiple regression in which attachment (continuous variable) was

regressed on the treatment indicator. In step 2, we aimed to partition each of the variables identified in the set of potential treatment moderators. The parameter stability tests used in this step are described in more detail in Zeileis et al. (2008). In step 3, when one of the partitioning variables had a p -value for the instability test below the pre-specified alpha value of .05, the partitioning variable with the lowest p -value was selected. The selected splitting value for that variable was taken to be the value that minimized the sum of squares in both partitions. We used default settings in the “partykit” R package and specified a minimum size of 30 respondents in each subgroup. Bonferroni corrected p -value was also applied to correct for multiple testing.

Results

After fitting the logistic generalized linear model with the family reunification outcome using MOB, we produced a decision tree (Figure 1). Table 2 shows the model parameters for each terminal node of the tree (i.e., subgroups). Node 1 includes all the participants. Participants were partitioned into two subgroups depending on the relationship of the caregiver with the child (non-kin vs. kin or permanent caregivers). The p -value ($p < .001$) from the parameter stability test indicated that the parameters of the treatment-outcome model were significantly different for these two subgroups.

In Figure 1, node 2 represents the subgroup of non-kin caregivers. These caregivers are further partitioned into two subgroups: those who scored 44 or lower (node 3) on the attachment subscale (DECA) and those who scored above 44 (node 4). Because node 3 is not further partitioned, it is a terminal node representing the subgroup of participants who were non-kin caregivers and scored 44 or lower on the attachment subscale. Node 4, another terminal node, represents the subgroup of non-kin caregivers with attachment subscale scores higher than 44. The p -value ($p < .01$) indicates that the parameters of the treatment-outcome model were

significantly different for the two subgroups. In both nodes 3 and 4, the odds ratio for reunification is higher in the treatment group compared to the control group (node 3 OR = 1.11; node 4 OR = 1.22).

Node 5 represents the subgroup of kin and permanent caregivers. This subgroup is further partitioned into two subgroups: those who we determined had a case history of physical abuse and those who did not. Terminal node 6 represents the subgroup of kin and permanent caregivers who had no case history of physical abuse. In this subgroup, the odds ratio for reunification was higher for the treatment group than for the control group (OR = 2.25). Terminal node 7 represents kin and permanent caregivers with a case history of physical abuse, and the odds ratio for reunification is lower in the treatment group than in the control group (OR = .86).

In summary, we found that three treatment moderators (i.e., caregivers' relationship to the child, attachment quality, and case history of physical abuse) interactively produced four subgroups of participants who responded differently to the intervention with regard to the reunification outcome. These four subgroups are: (a) non-kin caregivers with DECA attachment score 44 or below; (b) non-kin caregivers with DECA attachment score greater than 44; (c) kin and permanent caregivers with a case history of physical abuse; and (d) kin and permanent caregivers with no case history of physical abuse.

Table 2

Logistic Regression of Treatment Group (vs. Control) on the Likelihood of Reunification

Node		<i>B</i>	<i>SE</i>	<i>OR</i>
3	Non-kin caregivers, attachment score 44 and below	0.10	0.56	1.11
4	Non-kin caregivers, attachment score above 44	0.20	1.43	1.22
6	Kin or Perm caregivers, no physical abuse	0.81**	0.34	2.25
7	Kin or Perm caregivers, has physical abuse	-0.15	0.49	0.86

** $p < .01$

Figure 1. Odds ratio differences in reunification between treatment and control groups within subgroups of caregiver type, attachment level, and level of physical abuse.

Figure 2 visualizes the decision tree we produced after fitting the regression model with attachment (DECA) outcome using MOB, and Table 2 shows the model parameters for each terminal node of the tree (i.e., subgroups). In Figure 2, node 1 represents all the participants. This node is partitioned into two subgroups (terminal nodes 2 and 3) differentiated by the caregiver age variable, where $p < .01$ indicates that the parameters of the model differ significantly for the two subgroups. Node 2, a terminal node, represents caregivers aged up to 49 years old, while node 3 represents caregivers more than 49 years old. In node 2, the average score for attachment outcome at post-intervention is significantly higher in the treatment group than in the control group ($M = 3.13$, $SE = 1.32$, $p < .05$). In node 3 (also a terminal node), the average score for attachment outcome at post-intervention was lower in the treatment group than in the control group, but this difference was not significant ($M = -2.47$, $SE = 1.89$, $p = .19$).

In summary, one treatment moderator (caregivers' age) produced two subgroups of participants who responded differently to the intervention with regard to attachment (DECA) outcome. These two subgroups are (a) caregivers up to 49 years old, and (b) caregivers who are older than 49 years.

Table 3.
Linear Regression of Treatment Group (vs. Control) in Attachment Scores

Node		<i>B</i>	<i>SE</i>
2	Caregiver Age 49 years and younger	3.13*	1.32
3	Caregiver older than Age 49	-2.47	1.89

* $p < .05$

B = unstandardized beta

Figure 2. Subgroup differences in the unstandardized coefficients of attachment for caregivers at different ages

Note: Coefficients represent treatment group relative to the control groups).

Discussion

One key step of the Framework to Design, Test, Spread, and Sustain Effective Practice in Child Welfare is to explore treatment moderators in order to determine for whom the intervention was most and least effective (Framework Workgroup, 2014). To make this determination, our study explored treatment moderators of a trauma-informed parenting intervention for caregivers of young children in foster care. We also applied MOB, a novel data-driven technique, to identify key treatment moderators for two outcomes: the reunification of children with their caregivers and children's attachment relationship with their caregivers.

Reunification Outcomes

In our model of family reunification outcomes, results showed that children's relationship to their caregivers (kin, permanent, or non-kin caregivers) interacted with either caregivers' case history of physical abuse or pre-treatment attachment quality to form four distinct subgroups. Notably, each subgroup displayed statistically different model parameters. This finding corroborates prior studies that have observed the moderation of treatment effects by children's relationships to caregivers (kin or non-kin). For example, Sullivan et al. (2016) found that kin caregivers and non-kin caregivers of children improved differently in their ability to manage difficult child behaviors after participating in a trauma-informed parenting workshop. However, this result was not replicated in other studies using a similar outcome (e.g., Murray et al., 2019). One explanation for this inconclusive finding is that these studies used only one treatment moderator (i.e., relationship to caregivers) without exploring differences in treatment effects that may have derived from interactions of multiple treatment moderators. Our results indicate that interactions may occur with treatment moderators such as case history of physical abuse and pre-treatment attachment relationships between caregivers and children.

Pre-treatment attachment quality further differentiated two subgroups of non-kin caregivers: those with attachment scores at or below 44 and those above 44. Using a data-driven approach, our MOB analysis statistically determined an attachment score of 44 to be a splitting point between two subgroups with different treatment-outcome model parameters (an advantage of MOB is its ability to determine a cut-off score that can inform clinical assessments) However, given that our study was exploratory, further studies are needed to understand the clinical validity and utility of this cut-off score. In the present study, the raw score of 44 or $Z = -.24$ (standardized mean score = 0 and $SD = 1$) was close to the sample mean score. Therefore, one subgroup represented non-kin caregivers with lower-than-average attachment quality at pre-treatment and the other subgroup represented those with above-average attachment quality at pre-treatment.

A high-quality attachment to a caregiver is arguably the most significant factor impacting a child's safety and development, and is an essential consideration in permanency decisions (Goldsmith et al., 2004). In one study of a trauma-informed parenting intervention for children who experienced trauma, Ashton and colleagues (2016) found that caregivers' quality of pre-treatment attachment with their children influenced how much this attachment improved at postintervention. Our results suggest that pre-treatment attachment can also be a critical treatment moderator for reunification outcomes, but only for non-kin caregivers. Prior studies have indicated that a biological relationship between caregivers and children does not significantly affect the attachment between young children placed in foster care and their caregivers (e.g., Stovall & Dozier, 2000). Because many children in foster care are removed from their families and placed with non-kin caregivers, factors such as the duration of a pre-treatment placement could affect the attachment quality between non-kin caregivers and

children. Our results suggest that pre-treatment clinical assessments of the attachment quality between non-kin caregivers and their children can help identify a subgroup of non-kin caregivers with poorer attachment quality who may need higher treatment dosage in order to promote permanent placement.

For kin caregivers, reunification outcomes differed depending on whether the caregiver had a history of physical abuse at pre-treatment. However, caregivers' histories of child neglect did not appear to affect reunification outcomes. Researchers have found that different parenting interventions used in child welfare may be better than others for addressing specific types of child maltreatment (Pecora et al., 2014). For instance, programs based on the social learning theory specifically focus on changing parent-child interactions and are demonstrably effective in preventing the physical abuse of children (Vlahovicova et al., 2017). Further work is necessary for researchers and practitioners to understand whether and how the IB3 intervention has different effects on different types of child maltreatment.

Attachment Outcomes

Age-based subgroups (i.e., up to 49 years old and over 49 years old) differentiated caregiver's responses to the intervention in terms of the attachment outcome. Notably, in our review of treatment moderators in trauma-informed parenting interventions, no study examined caregivers' age. Our results suggest that caregivers' age may be a potential treatment moderator, particularly among caregivers at least 50 years old. Indeed, prior research has found that older caregivers may be more engaged in parenting interventions and have higher attendance, though results are inconclusive (Muzik et al., 2014). Other parenting studies have found that older caregivers are more likely than younger mothers to demonstrate a positive parenting style. However, in our study, younger caregivers (i.e., 49 years old or younger) responded better than

older caregivers (50 years and above) to the intervention. One possible explanation is that most relevant studies have not further differentiated the age bands (e.g., 30-40; 40-50; 50-60) for caregivers above 30 years of age. For example, Kim et al. (2018) compared younger caregivers with caregivers aged 30 and above. The present study suggests that caregivers aged 50 and older may require different types or features of interventions from younger caregivers in order to optimize their response to the interventions. Unlike our findings regarding the family reunification outcome, we found no evidence that a caregiver's relationship to the child (i.e., kin or permanent relationship) was a treatment moderator of attachment, further supporting earlier findings that biological relationship is not predictive of caregiver-child attachment.

We also identified several factors that did not moderate the effectiveness of the intervention, including characteristics of the child (e.g., race, age, sex, presence of emotional or behavioral problems) and the caregiver (race, sex, education, employment status, sources of support received, and receipt of parenting services). These results align with some studies of trauma-informed interventions that found no differences in treatment effects based on parents' and children's sociodemographic characteristics such as age, gender, and race (Murray et al., 2019; Price et al., 2015). Our results suggest that groups of caregivers and their children across these characteristics may not have distinct across-group differences in their response to trauma-informed parenting intervention in IB3.

Limitations. At the same time, MOB has several limitations when used to identify treatment moderators as a way of defining subgroups of participants that benefit differently from an intervention. First, characteristics within identified subgroups may not be balanced across treatment and control groups even if the balance of these characteristics is verified for the entire sample (VanderWeele & Knol, 2011). In our post-analysis investigation, we examined the extent

of covariate balance between the treatment and control groups within each subgroup using standardized mean differences (SMD; Austin, 2011). We found that a few covariates had a SMD greater than 0.20 across subgroups – the conventional indication of covariate imbalance. For instance, for node 3 in Figure 1, we found that four covariates (i.e., child race, caregiver education, prior receipt of parenting services, and neighborhood quality) had SMD values ranging from .24 to .27. Thus, in the present study, any interpretation of treatment effects across treatment groups in each subgroup must consider the potential effects of confounders.

Fortunately, methods exist to address potential covariate imbalance issues within subgroups. For instance, Shepherd-Banigan et al. (2020) used the mCART method to balance covariates between matched pairs of treatment and control respondents in order to ensure that subgroups identified by the MOB were balanced on covariates. Since the primary aim of our study is to identify treatment moderators that differentiate subgroups, interested readers can find further discussions of robust estimation of treatment effects within subgroups in Rigdon et al. (2018). The second shortcoming of MOB is the tendency for decision tree models to overfit the data. To prevent overfitting in our study, which modeled only a single decision tree, we used pre-pruning methods based on Bonferroni-corrected p -values from the score-based fluctuation tests (Zeileis & Hothorn, n.d.). Other methods such as random forest or 10-fold cross-validation may also be used to address potential issues of over-fitting (Garge et al., 2013).

A more general limitation of our study is that our results are exploratory and require further validation before being implemented in practice. Future investigations should explore sample stratifications based on the moderators identified in the present study (i.e., caregivers' relationship to the child, pre-treatment attachment quality, history of physical abuse, and age of caregivers) in order to help validate our findings. Finally, due to incomplete data, we did not

include other potential moderators of trauma-informed parenting interventions in our pool of 21 treatment moderators. For instance, due to the amount of missing pertinent data, we did not include caregivers' marital status, financial difficulties, and caregivers' psychological health (e.g., depression; Friedrich et al., 1992) in our pool of moderators despite their potential relevance to our analyses.

Conclusion

Despite these limitations, our study provides useful insights into possible treatment moderators that bring to light certain subgroups that benefit differently from trauma-focused parenting interventions. It is important for researchers and practitioners to understand which groups of families or individuals may benefit differently from an intervention. This point echoes scholars' observations that a universal policy of teaching parenting skills to parents is insufficient to improving child welfare outcomes among all families. Rather, treatment planning must account for the varying characteristics of families, such as family dynamics and cultural or ethnic norms, in determining the optimal intervention protocol (Pecora et al., 2014). In the present study, we found that caregivers' relationship status, their age, caregiver-child attachment quality, and their histories of physical abuse were important treatment moderators of trauma-informed parenting interventions, meaning that future trauma-informed interventions should consider these moderators when planning their programming for specific caregivers and children.

Our study's novel use of MOB helped us identify these key treatment moderators and their patterns of interaction in moderating the effects of the intervention. Although MOB is a data-driven method that avoids the limitations of conventional moderator analyses, it has a demonstrable ability to incorporate a parametric model in order to represent a theory-driven hypothesis, making it a highly useful tool for future social sciences research.

References

- Aardoom, J. J., Dingemans, A. E., Fokkema, M., Spinhoven, P., & Van Furth, E. F. (2017). Moderators of change in an Internet-based intervention for eating disorders with different levels of therapist support: What works for whom? *Behaviour Research and Therapy*, 89, 66–74. <https://doi.org/10.1016/j.brat.2016.11.012>
- Ashton, C. K., O'Brien-Langer, A., & Silverstone, P. H. (2016). The CASA Trauma and Attachment Group (TAG) Program for Children who have Attachment Issues Following Early Developmental Trauma. *Journal of the Canadian Academy of Child and Adolescent Psychiatry*, 25(1), 35–42.
- Austin, P. C. (2011). An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies. *Multivariate Behavioral Research*, 46(3), 399–424. <https://doi.org/10.1080/00273171.2011.568786>
- Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173–1182. <https://doi.org/10.1037/0022-3514.51.6.1173>
- Cohen, J. A., Deblinger, E., Mannarino, A. P., & Steer, R. A. (2004). A Multisite, Randomized Controlled Trial for Children With Sexual Abuse–Related PTSD Symptoms. *Journal of the American Academy of Child & Adolescent Psychiatry*, 43(4), 393–402. <https://doi.org/10.1097/00004583-200404000-00005>
- Cook, A., Spinazzola, J., Ford, J., Lanktree, C., Blaustein, M., Cloitre, M., DeRosa, R., Hubbard, R., Kagan, R., Liautaud, J., Mallah, K., Olafson, E., & van der Kolk, B. (2005). Complex Trauma in Children and Adolescents. *Psychiatric Annals*, 35(5), 390–398. <https://doi.org/10.3928/00485713-20050501-05>

- Deblinger, E., Stauffer, L. B., & Steer, R. A. (2001). Comparative Efficacies of Supportive and Cognitive Behavioral Group Therapies for Young Children Who have been Sexually Abused and their Nonoffending Mothers: *Child Maltreatment*, 6.
<https://doi.org/10.1177/1077559501006004006>
- Driessen, E., Smits, N., Dekker, J. J. M., Peen, J., Don, F. J., Kool, S., Westra, D., Hendriksen, M., Cuijpers, P., & Van, H. L. (2016). Differential efficacy of cognitive behavioral therapy and psychodynamic therapy for major depression: A study of prescriptive factors. *Psychological Medicine*, 46(4), 731–744. <https://doi.org/10.1017/S0033291715001853>
- Framework Workgroup. (2014). *A Framework To Design, Test, Spread, and Sustain Effective Practice in Child Welfare* (p. 33). Children’s Bureau, Administration for Children and Families, U.S. Department of Health and Human Services.
https://www.acf.hhs.gov/sites/default/files/cb/pii_ttap_framework.pdf
- Fraser, J. G., Lloyd, S., Murphy, R., Crowson, M., Zolotor, A. J., Coker-Schwimmer, E., & Viswanathan, M. (2013). A Comparative Effectiveness Review of Parenting and Trauma-Focused Interventions for Children Exposed to Maltreatment. *Journal of Developmental & Behavioral Pediatrics*, 34(5), 353–368.
<https://doi.org/10.1097/DBP.0b013e31828a7dfc>
- Frazier, P. A., Tix, A. P., & Barron, K. E. (2004). Testing Moderator and Mediator Effects in Counseling Psychology Research. *Journal of Counseling Psychology*, 51(1), 115–134.
<https://doi.org/10.1037/0022-0167.51.1.115>
- Friedrich, W., Luecke, W., Beilke, R., & Place, V. (1992). Psychotherapy Outcome of Sexually Abused Boys: An Agency Study. *Journal of Interpersonal Violence*, 7.
<https://doi.org/10.1177/088626092007003008>

- Gardner, F., Hutchings, J., Bywater, T., & Whitaker, C. (2010). Who Benefits and How Does It Work? Moderators and Mediators of Outcome in an Effectiveness Trial of a Parenting Intervention. *Journal of Clinical Child & Adolescent Psychology*, 39(4), 568–580. <https://doi.org/10.1080/15374416.2010.486315>
- Garge, N. R., Bobashev, G., & Eggleston, B. (2013). Random forest methodology for model-based recursive partitioning: The mobForest package for R. *BMC Bioinformatics*, 14(1), 125. <https://doi.org/10.1186/1471-2105-14-125>
- Goldsmith, D. F., Oppenheim, D., & Wanlass, J. (2004). Separation and Reunification: Using Attachment Theory and Research to Inform Decisions Affecting the Placements of Children in Foster Care. *Juvenile and Family Court Journal*, 55(2), 1–13. <https://doi.org/10.1111/j.1755-6988.2004.tb00156.x>
- Graham-Bermann, S. A., & Miller-Graff, L. (2015). Community-based intervention for women exposed to intimate partner violence: A randomized control trial. *Journal of Family Psychology*, 29(4), 537–547. <https://doi.org/10.1037/fam0000091>
- Hayes, A. F. (2018). *Introduction to Mediation, Moderation, and Conditional Process Analysis* (2nd ed.). Guilford Press.
- Horwitz, S. M., Chamberlain, P., Landsverk, J., & Mullican, C. (2010). Improving the Mental Health of Children in Child Welfare Through the Implementation of Evidence-Based Parenting Interventions. *Administration and Policy in Mental Health and Mental Health Services Research*, 37(1), 27–39. <https://doi.org/10.1007/s10488-010-0274-3>
- Hothorn, T., & Zeileis, A. (2015). Partykit: A modular toolkit for recursive partytioning in R. *The Journal of Machine Learning Research*, 16(1), 3905–3909.

- Illinois Department of Children and Family Services. (2018). *Final Evaluation Report Illinois Birth through Three Waiver: Child and Family Intervention* (p. 166). The Illinois Department of Children and Family Services.
https://www2.illinois.gov/dcf/aboutus/newsandreports/Documents/IL_IB3_Final_Evaluation_Report_Dec_2018.pdf
- Kim, T. H. M., Connolly, J. A., Rotondi, M., & Tamim, H. (2018). Characteristics of positive-interaction parenting style among primiparous teenage, optimal age, and advanced age mothers in Canada. *BMC Pediatrics*, 18(1), 2. <https://doi.org/10.1186/s12887-017-0972-z>
- Kiser, L. J., Backer, P. M., Winkles, J., & Medoff, D. (2015). Strengthening Family Coping Resources (SFCR): Practice-based evidence for a promising trauma intervention. *Couple and Family Psychology: Research and Practice*, 4(1), 49–59.
<https://doi.org/10.1037/cfp0000034>
- Kopf, J., Augustin, T., & Strobl, C. (2010). *The potential of model-based recursive partitioning in the social sciences – Revisiting Ockham’s Razor* (Technical No. 88; p. 25). Department of Statistics, University of Munich.
- Kotch, J. B., Browne, D. C., Dufort, V., Winsor, J., & Catellier, D. (1999). Predicting child maltreatment in the first 4 years of life from characteristics assessed in the neonatal period. *Child Abuse & Neglect*, 23(4), 305–319. [https://doi.org/10.1016/S0145-2134\(99\)00003-4](https://doi.org/10.1016/S0145-2134(99)00003-4)
- Kraemer, H., Frank, E., & Kupfer, D. (2006). Moderators of Treatment Outcomes: Clinical, Research, and Policy Importance. *JAMA*, 296(10), 1286–1289.
<https://doi.org/10.1001/jama.296.10.1286>

- Kraemer, H., Wilson, G., Fairburn, C., & Agras, W. (2002). Mediators and Moderators of Treatment Effects in Randomized Clinical Trials. *Archives of General Psychiatry*, 59(10), 877–883. <https://doi.org/10.1001/archpsyc.59.10.877>
- Lindstrom, S., Elam, K., Rogers, A. A., & Hilley, C. (2018). A Meta-Analysis of Parenting Practices and Child Psychosocial Outcomes in Trauma-Informed Parenting Interventions after Violence Exposure. *Prevention Science*, 19(7), 927–938. <https://doi.org/10.1007/s11121-018-0943-0>
- Murray, K. J., Sullivan, K. M., Lent, M. C., Chaplo, S. D., & Tunno, A. M. (2019). Promoting trauma-informed parenting of children in out-of-home care: An effectiveness study of the resource parent curriculum. *Psychological Services*, 16(1), 162–169. <https://doi.org/10.1037/ser0000324>
- Muzik, M., Schmicker, M., Alfafara, E., Dayton, C., Schuster, M., & Rosenblum, K. (2014). Predictors of Treatment Engagement to the Parenting Intervention Mom Power Among Caucasian and African American Mothers. *Journal of Social Service Research*, 40(5), 662–680. <https://doi.org/10.1080/01488376.2014.917451>
- Pecora, P. J., Sanders, D., Wilson, D., English, D., Puckett, A., & Rudlang-Perman, K. (2014). Addressing common forms of child maltreatment: Evidence-informed interventions and gaps in current knowledge: Interventions for child maltreatment. *Child & Family Social Work*, 19(3), 321–332. <https://doi.org/10.1111/cfs.12021>
- Powell, G., Mackrain, M., & LeBuffe, P. (2007). *Devereux Early Childhood Assessment for Infants and Toddlers Technical Manual* (p. 54). The Devereux Foundation.
- Price, J. M., Roesch, S., Walsh, N. E., & Landsverk, J. (2015). Effects of the KEEP Foster Parent Intervention on Child and Sibling Behavior Problems and Parental Stress During a

- Randomized Implementation Trial. *Prevention Science*, 16(5), 685–695.
<https://doi.org/10.1007/s11121-014-0532-9>
- Rigdon, J., Baiocchi, M., & Basu, S. (2018). Preventing false discovery of heterogeneous treatment effect subgroups in randomized trials. *Trials*, 19(1), 382.
<https://doi.org/10.1186/s13063-018-2774-5>
- Seibold, H., Zeileis, A., & Hothorn, T. (2016). Model-Based Recursive Partitioning for Subgroup Analyses. *The International Journal of Biostatistics*, 12(1), 45–63.
<https://doi.org/10.1515/ijb-2015-0032>
- Shepherd-Banigan, M., Smith, V. A., Lindquist, J. H., Cary, M. P., Miller, K. E. M., Chapman, J. G., & Van Houtven, C. H. (2020). Identifying treatment effects of an informal caregiver education intervention to increase days in the community and decrease caregiver distress: A machine-learning secondary analysis of subgroup effects in the HI-FIVES randomized clinical trial. *Trials*, 21(1), 189. <https://doi.org/10.1186/s13063-020-4113-x>
- Stovall, K. C., & Dozier, M. (2000). The development of attachment in new relationships: Single subject analyses for 10 foster infants. *Development and Psychopathology*, 12(2), 133–156. <https://doi.org/10.1017/S0954579400002029>
- Strobl, C., Malley, J., & Tutz, G. (2009). An introduction to recursive partitioning: Rationale, application, and characteristics of classification and regression trees, bagging, and random forests. *Psychological Methods*, 14(4), 323–348.
<https://doi.org/10.1037/a0016973>
- Sullivan, K. M., Murray, K. J., & Ake, G. S. (2016). Trauma-Informed Care for Children in the Child Welfare System: An Initial Evaluation of a Trauma-Informed Parenting Workshop. *Child Maltreatment*, 21(2), 147–155. <https://doi.org/10.1177/1077559515615961>

- Thurston, H., & Miyamoto, S. (2018). The use of model based recursive partitioning as an analytic tool in child welfare. *Child Abuse & Neglect*, 79, 293–301.
<https://doi.org/10.1016/j.chiabu.2018.02.012>
- U.S. Department of Health and Human Services. (2018). *The AFCARS report: Preliminary FY 2018* (No. 25; p. 6). Department of HHS.
<https://www.acf.hhs.gov/sites/default/files/cb/afcarsreport25.pdf>
- VanderWeele, T. J., & Knol, M. J. (2011). Interpretation of subgroup analyses in randomized trials: Heterogeneity versus secondary interventions. *Annals of Internal Medicine*, 154(10), 680–683. <https://doi.org/10.7326/0003-4819-154-10-201105170-00008>
- Vlahovicova, K., Melendez-Torres, G. J., Leijten, P., Knerr, W., & Gardner, F. (2017). Parenting Programs for the Prevention of Child Physical Abuse Recurrence: A Systematic Review and Meta-Analysis. *Clinical Child and Family Psychology Review*, 20(3), 351–365.
<https://doi.org/10.1007/s10567-017-0232-7>
- Zeileis, A., & Hothorn, T. (n.d.). *Parties, Models, Mobsters: A New Implementation of Model-Based Recursive Partitioning in R*. <https://cran.r-project.org/web/packages/partykit/vignettes/mob.pdf>
- Zeileis, A., Hothorn, T., & Hornik, K. (2008). Model-Based Recursive Partitioning. *Journal of Computational and Graphical Statistics*, 17(2), 492–514.
<https://doi.org/10.1198/106186008X319331>