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Examining Placement Disruption in Child Welfare

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Child welfare systems in the United States are increasingly focused on reducing the number of children who come into care, reducing the length of time that those children are in care, and reducing the use of more restrictive placements such as residential treatment. In this context, child welfare systems are increasingly interested in supporting placement decision making with standardized assessments and decision tools. The current article describes an analysis of information from the Tennessee child welfare system demonstrating that the placements of children whose first placement is consistent with an assessment-based decision support algorithm are more stable than the placements of children whose first placement is not consistent with the algorithm recommendation. These results add to the growing body of literature suggesting that such

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decision supports are associated with improved outcomes and the implications for child welfare system design are briefly discussed.

KEYWORDS *child welfare, foster home care, residential treatment, placement disruption*

INTRODUCTION

Child welfare systems in the United States are now focused more than ever before on reducing the number of children who come into care, reducing the length of time that those children are in care, and reducing the use of more restrictive placements such as residential treatment (Baker, Wulczyn, & Dale, 2005; Wulczyn, Kogan, & Harden, 2003). A number of policy initiatives have been undertaken to help accomplish these goals (Wulczyn & Orlebeke, 2000; Wulczyn, 2005). For example, the U. S. Department of Health and Human Services, Administration for Children and Families, Children's Bureau has the authority to offer Child Welfare Waiver Demonstration to provide states with an opportunity to use federal funds more flexibly so that they can implement innovative ideas to improve the aforementioned and other child welfare outcomes (http://www.acf.hhs.gov/programs/cb/programs/child-welfare-waivers).

One thing that the focus on these and related outcomes such as placement stability has brought to the forefront of the conversation is the need to intentionally engineer child welfare systems to promote effective decision-making (Munro, 2005b; Cull, Rzepnicki, O'Day, & Epstein, 2013; Munro, 2005a; Rzepnicki et al., 2010). The field increasingly recognizes that the phenomena that affect human decision-making more generally, phenomena such as selective attention, group think, and decision fatigue to name just a few potentially relevant biases (Croskerry, 2002; Ramser, 1993; Samuelson & Zeckhauser, 1988), are also likely to bias child welfare decision-making.

Other industries such as aviation and healthcare have embraced the idea that strategies such as using standardized assessment has the potential to reduce biased decision-making and improve outcomes (Gawande, 2009; Gordon, Mendenhall, & O'Connor, 2012; Haynes et al., 2009). For example, the idea that implementing checklists (Gawande, 2009), which can be considered a "simple" form of standardized assessment, has now gained wide acceptance not just for its potential to help manage complexity in healthcare environments such as operating rooms, but also for its potential to manage other complicated situations that require highly reliable operations (Vogus, Sutcliffe, & Weick, 2010).

Specific to child welfare placement decision-making, which inevitably includes decisions about whether or not to place children in residential treatment centers. Existing literature provides preliminary evidence that using standardized assessment for decision support can help improve system performance (Lyons, Epstein, & Jordan, 2010). There is a growing body of evidence that placements based on decisions that are congruent with decision support algorithms based on standardized assessments of a child and his or her family's needs appear more likely to achieve positive outcomes than are decisions that are incongruent with the recommendations of such algorithms (Chor, McClelland, Weiner, Jordan, & Lyons, 2015, 2012). The current study seeks to contribute to this growing body of evidence by examining whether algorithm-consistent placements are more stable—that is, less likely to disrupt—than algorithm-inconsistent placements among a cohort of children in the Tennessee child welfare system.

METHODS

Design

This longitudinal study was conducted using administrative and assessment information from the Tennessee Department of Children's Services (TDCS) for all child welfare episodes for children between the ages of 5 and 19 years who entered Tennessee state custody between April 2010 and May 2015 (n = 14718 child welfare episodes for 13920 unique children). Data elements include child demographic characteristics, placement information, and information from the TDCS intake assessment of child and family needs and strengths. This project was reviewed and approved by the TDCS Research Review Committee and Vanderbilt University Institutional Review Board.

Measures

Child demographic variables include child age, race, gender, and Grand Region. Categorical variables were dummy-coded.

Each child welfare episode includes one or more placements. TDCS categorizes placements according to their level of restrictiveness into "levels" that are roughly equivalent to kinship/foster care (level 1), therapeutic foster care (level 2), congregate care/residential treatment (level 3), and subacute hospital/inpatient care (level 4). For purposes of the current study, levels 3 and 4 are combined into one level (e.g., level 3/4) because of the small number of subacute hospital/inpatient care placements. TDCS staff categorized placement dyads as being considered placement disruptions (e.g., moves to a higher "level" of care) or not.

The Child and Adolescent Needs and Strengths (CANS) is the assessment of child and family needs and strengths used by TDCS at intake and for reassessment over the life of the custody episode (Lyons, 1999). By TDCS protocol, CANS ratings are made by TDCS case managers who receive annual training and certification as CANS raters at or above 70% reliability in comparison to standardized training vignettes. Training, certification and technical assistance using the CANS for this purpose is provided to TDCS by consultants from the Vanderbilt University Center of Excellence for Children in State Custody.

Previous research demonstrates that the CANS has adequate inter-rater and internal consistency reliability and concurrent, discriminant, and predictive validity (Anderson, Lyons, Giles, Price, & Estle, 2003; Epstein, Bobo, Cull, & Gatlin, 2011; Epstein, Jordan, Rhee, McClelland, & Lyons, 2009; He, Lyons, & Heinemann, 2004; Leon, Lyons, & Uziel-Miller, 2000; Leon et al., 2000; Park, Jordan, Epstein, Mandell, & Lyons, 2009). The CANS is currently used to support service planning decisions and for outcomes measurement in child welfare and child behavioral health service systems in many states (Lyons, 2009; Lyons & Weiner, 2009; Lyons, 2004).

The version of the CANS used by TDCS contains 65 items that are each rated on a 4-point scale ranging from 0 to 3 with a rating of "0" indicating no evidence of need for services and a rating of "3" indicating need for immediate or intensive services. TDCS has implemented a decision support algorithm that recommends a level of placement for each child based on his or her level of need. Similarly to placements, placement level recommendations are categorized in one of four levels that are also roughly equivalent to kinship/foster care (level 1), therapeutic foster care (level 2), congregate care/residential treatment (level 3), and subacute hospital/inpatient care (level 4).

Variable Definitions

These data were used to define our outcome variable, primary predictor variable, and covariates. Placement disruption, our outcome variable, were defined by TDCS placement staff by categorizing first placement/second placement dyads as being a move from one level of care to a higher level of care (disruption) or not (not disruption). Thus, "events" were defined as placement disruptions and the "time to event" was defined as the number of days from the beginning of first to the beginning of the second placement in each dyad. Records that were missing second placement dates were censored on the date of the end of the custody episode or, if that were also unavailable, the record was censored at May 3, 2015.

Our primary predictor variable was defined as a binary indicator variable specifying whether or not the first placement in the dyad was consistent with the CANS-based decision support algorithm or inconsistent with that algorithm.

Covariates included the level of the first placement (1, 2, or 3/4), age in years, race (white, black, or other), gender (female, male), and Grand

Region of the state in which the custody episode originated (East TN, Middle TN, West TN).

Analysis

All analyses were conducted using R software version 3.0.1 (cran.r-project.org). Descriptive statistics were reported using means and standard deviations for continuous variables and frequencies and percentages for categorical variables. A Kaplan-Meier plot is included to visually illustrate unadjusted results comparing risk of placement disruption for algorithm consistent and inconsistent placements.

For our multivariate analysis, we built a Cox proportional hazards model to examine risk of placement disruption for children receiving an algorithm-consistent first placement in the dyad as compared to children receiving an algorithm-inconsistent first placement in the dyad, adjusting for the aforementioned covariates. We determined that the data sufficiently met the proportional hazards assumption underlying this model through the examination of a log-log plot. Confidence intervals for the parameters were calculated using cluster-robust standard errors because individual children were allowed to have multiple custody episodes in the study time period (Rogers, 1993).

Results

The analytic cohort comprised first placement and second placement dyads for 13920 unique children with 14718 custody episodes. Individual children could have multiple custody episodes in the study timer period. Descriptive statistics are provided in Table 1. On average, children were approximately

TABLE 1 Descriptive Statistics of Study Sample, Unique Children

Variable	Value (n = 13920)
Child age in years, *M* (*SD*)	11.13 (4.20)
Child race, # (%)	
Black	2820 (20.26%)
White	8426 (60.53%)
Other	580 (4.17%)
Missing	2094 (15.04%)
Child Gender, # (%)	
Female	6874 (49.38%)
Male	7046 (50.62%)
Missing	0 (0.00%)
Grand Region, # (%)	
East	4666 (33.52%)
Middle	3444 (24.74%)
West	2129 (15.30%)
Missing	3681 (26.44%)

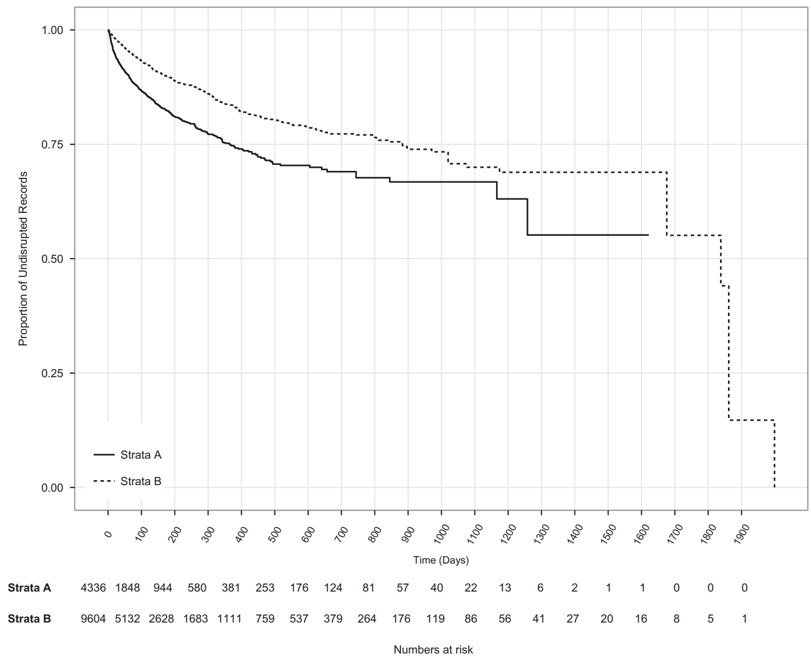

FIGURE 1 Kaplan-Meier Plots stratified by algorithm adherence.

11 years old. Approximately 61% were white, roughly half were girls, and the largest percentage (nearly 34%) came from the Eastern part of the state.

Figure 1 represents an unadjusted Kaplan-Meier curve representing the product limit estimator of the hazard functions for dyads that were not algorithm consistent and those that were consistent. In Figure 1, Strata A depicts algorithm inconsistent placements and Strata B depicts algorithm consistent placements.

Table 2 displays the results of the multivariate Cox proportional hazards model described above. Notably, we see that the hazard ratio of disruption comparing an algorithm consistent placement to that of an algorithm inconsistent placement is 0.74 (95% CI: 0.66, 0.83) after adjusting for the other covariates and suggesting that algorithm consistent placements are significantly less likely to disrupt than algorithm inconsistent placements.

Discussion

Results suggest that risk of disruption was lower for algorithm-consistent placements than for algorithm-inconsistent placements after adjusting for the restrictiveness of the first placement in each first placement—second placement dyad and other factors. This finding is generally consistent with prior work showing that decision support algorithm consistent placements

TABLE 2 Results of Cox Proportional Hazards Model

Variable	HR	95% CI		*p*-value
Algorithm consistent placement (ref: inconsistent)	0.74	0.66	0.83	< 0.01
Initial placement level (ref: level 1)				
2	1.92	1.64	2.25	< 0.01
3 or 4	1.91	1.61	2.27	< 0.01
Age in year	1.04	1.02	1.06	< 0.01
Race (ref: black)				
White	0.80	0.57	1.13	0.20
Other	0.84	0.72	0.99	0.03
Male (ref: female)	0.92	0.81	1.04	0.19
Grand region (ref: East)				
Middle	1.19	1.04	1.37	0.01
West	0.84	0.70	1.01	0.06

are associated with positive outcomes relative to decision support algorithm inconsistent placements (Chor et al., 2015, 2012). Other notable factors also associated with increased risk for disruption include restrictiveness of the first placement in the first placement—second placement dyad (with less restrictive levels of care associated with greater risk of disruption) and child age (with each year of increasing age associated with a 4% increase in risk). In addition, risk of disruption differed between different parts of the state with Middle Tennessee having a higher risk of disruption and West Tennessee a lower risk of disruption in comparison to East Tennessee.

These findings add support to the growing body of literature indicating that decisions made consistently with algorithms based on information from standardized assessment of child and family needs and strengths may be associated with better outcomes than are algorithm-inconsistent decisions. This information is potentially important for residential treatment because in at least two ways. First, although the association between the "level" of the first placement and disruption risk was not the focus of this article, we did show that in comparison to children in the "level" of care roughly equivalent to foster care, children whose first placement was in the "level" of care roughly equivalent to residential care were more likely to disrupt. This is important because it provides some support for the idea that the children referred to residential care may represent a unique sub-group. Second, the finding suggests that similar strategies could be used by residential treatment centers to guide their decisions about which children to admit to their programs. Many variables factor into such decisions and it is possible that information from decision support algorithms could improve admission decisions.

For child welfare systems more generally, the findings of the current study are important because they suggest that child welfare systems should not only implement standardized assessment so that they have a measure and in some cases their required measure of child well-being, but that child welfare systems may want to consider regarding the implementation of standardized assessment as an intervention to support decision making (proximally) and improve system performance (more distally). Prospective examination of the impact of implementing these types of interventions on child welfare system performance is urgently needed.

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