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Patterns of out-of-home placement decision-making in child welfare☆

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ABSTRACT

Out-of-home placement decision-making in child welfare is founded on the best interest of the child in the least restrictive setting. After a child is removed from home, however, little is known about the mechanism of placement decision-making. This study aims to systematically examine the patterns of out-of-home placement decisions made in a state's child welfare system by comparing two models of placement decision-making: a multidisciplinary team decision-making model and a clinically based decision support algorithm. Based on records of 7816 placement decisions representing 6096 children over a 4-year period, hierarchical log-linear modeling characterized concordance or agreement, and discordance or disagreement when comparing the two models and accounting for age-appropriate placement options. Children aged below 16 had an overall concordance rate of 55.7%, most apparent in the least restrictive (20.4%) and the most restrictive placement (18.4%). Older youth showed greater discordant distributions (62.9%). Log-linear analysis confirmed the overall robustness of concordance (odd ratios [ORs] range: 2.9–442.0), though discordance was most evident from small deviations from the decision support algorithm, such as one-level under-placement in group home (*OR* = 5.3) and one-level over-placement in residential treatment center (*OR* = 4.8). Concordance should be further explored using child-level clinical and placement stability outcomes. Discordance might be explained by dynamic factors such as availability of placements, caregiver preferences, or policy changes and could be justified by positive child-level outcomes. Empirical placement decision-making is critical to a child's journey in child welfare and should be continuously improved to effect positive child welfare outcomes.

Introduction

In sound child welfare practice, out-of-home placement decision-making is founded on the best interest of the child in the least restrictive setting that meets the child's placement needs with appropriate services and treatments (Snyder, Lawrence,

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& Dodge, 2012; Sunseri, 2005). While there is a substantial body of research on decision-making associated with removing children from home (Berger, Bruch, Johnson, James, & Rubin, 2009) due to trauma, domestic abuse, neglect, or violence, or unstable or unsafe home environments (Armour & Schwab, 2007; Barth et al., 2007; Hyde & Kammerer, 2009), less is known about placement decision-making after the children are removed from home and enter out-of-home placements. Although a bottom-up approach, such as characterizing child welfare profiles (Armour & Schwab, 2007) or developing interventions for the child welfare population (Fisher & Chamberlain, 2000) provides important knowledge to the field, a top-down approach in understanding how and where children get placed is equally significant to prevention and treatment (Blakey et al., 2012; Chor, McClelland, Weiner, Jordan, & Lyons, 2012).

Although there are limited data specific to placement decisions in the child welfare system, the resulting distributions of out-of-home placements serve as relevant proxies. In 2011, there were over 400,000 children in the foster care system in the United States, of whom 74% were placed in foster home (47% kinship, 27% non-kinship), 9% in residential treatment center, 6% in group home, 5% in trial home, and 4% in pre-adoptive home (HHS, 2012). These placement distributions have been relatively stable since 2009 (HHS, 2010, 2011).

Although the national distributions out-of-home placements are informative, it is less clear how a child ends up in one type of placement versus another, and what information and circumstances guide the placement decision-making. State and county child welfare systems have specific mechanisms in place for placement decision-making, including Arizona (Arizona Department of Health Services, 2009), Hawaii (Daleiden, 2004), Wisconsin (Wisconsin Department of Children & Families, 2011a;Wisconsin Department of Children & Families, 2011b), and Los Angeles County in California (Los Angeles County Department of Children & Family Services, 2009), though they have not been systematically studied. Hence, an emerging policy and research gap is informing good placement practice through the use of placement guidelines and criteria. The same sense of responsibility that ensures children's well-being through removal from unsafe home environments should accompany subsequent out-of-home placement decision-making.

There is some derivative knowledge regarding the complex process of out-of-home placement decision-making in child welfare, which is best captured by the Decision-Making Ecology Framework (Baumann, Dalgleish, Fluke, & Kern, 2011; Fluke, Chabot, Fallon, MacLaurin, & Blackstock, 2010). First, placement decision-making is often the product of a variety of multilevel factors (Baumann et al., 2011). A child's future placement might be influenced by the individual case factors, such as child's placement history, availability of bed space, geographic limitations, and policy demands (Crea, Usher, & Wildfire, 2009; James, 2004; Lindsey, 1992; Martin, Peters, & Glisson, 1998). Second, most state child welfare systems consider out-of-home placement stability a priority and are invested in identifying approaches to increase placement stability such as placement-matching (Blakey et al., 2012). These efforts represent external and systemic factors that have a direct impact on out-of-home placement decision-making policy. Of note, individual case factors such as age can have direct interactions with external and systemic factors. For instance, in the conventional practice of the least restrictive setting, it is more relevant to older children who have a greater possibility of entering institutional care than younger children whose primary concern is community stabilization in settings such as foster home or kinship care that provide a comparable level of attachment and care that a biological home environment would have provided. Third, to bridge research and practice, there is a continuing need to clarify the relationships and pathways between behavioral problems, specifically risk and trauma (Griffin, Martinovich, Gawron, & Lyons, 2009), and out-of-home placements during entry and transition in the child welfare system (Aarons et al., 2010; Berger et al., 2009). Further, placement decision-making as a form of clinical decision-making can lend itself to individual decision-maker biases and inconsistencies. For instance, given the myriad of guidelines and standards for placement, individual discretion of caseworkers remains a critical component of the decision-making process (Bickman, Karver, & Schut, 1997). When experience and efficiency guide placement decision-making, caseworkers might favor confirmatory information consistent with their placement hypothesis or develop convenient associations between key variables in clinical history (Benbenishty & Chen, 2003; Monnickendam, Savaya, & Waysman, 2005). In sum, the interactions among these multilevel factors can lead to variability in the out-of-home placement decisions made and subsequent outcomes. However, a core lesson remains clear – placement decision-making early on in a child's stay in care has ramifications on the child's subsequent placement trajectories and outcomes.

Of the system-level factors in the Decision-Making Ecology Framework, there are generally two models that support child welfare placement decision-making: (a) a multidisciplinary team model and (b) a decision support algorithm model. Multidisciplinary models have roots in the special education field (e.g., Individual Education Program; Pfeiffer & Naglieri, 1983) before they evolved in child welfare and child protection (DeMuro & Rideout, 2002; Leeson, 2007). Multidisciplinary teams pool together diverse expertise and involve the child in the decision-making process. For example, the Annie E. Casey Foundation multidisciplinary team decision-making model has been implemented in over 60 child welfare agencies in 17 states (Crea et al., 2009). There is also evidence of improved connection to mental health services among children who experienced team decision-making (Weigensberg, Barth, & Guo, 2009). However, the complexity of the multidisciplinary processes faces challenges in standardization and measurement (Frost & Robinson, 2007) and in implementation (Crampton, Crea, Abramson-Madden, & Usher, 2008).

A decision-making algorithm specific to out-of-home placement decision-making is generally defined as "a logical set of criteria that describes the clinical characteristics of children and families that would be best served by the available decision options relevant to the algorithm" (Lyons, 2004, p. 158) such that the criteria for placement are needs- and strengths-based (Lyons & Abraham, 2001). Early versions of decision support algorithms focused on matching incoming children to known demographic profiles of existing placements (Schwab, Bruce, & Mcroy, 1984). More recently, they have become more clinically focused using placement criteria and multidimensional assessments (Durbin, Cochrane, Goering, & Macfarlane, 2001; Lyons, 2004).

The development of a decision support algorithm generally involves defining a continuum of level of care from least to most restrictive and operationalizing placement criteria for each level of care (Durbin et al., 2001; Srebnik, Uehara, & Smukler, 1998). Similar to the challenges faced by multidisciplinary processes, implementation efforts associated with decision support algorithms vary by states, and not all field-tested algorithms have been applied in practice (Doran & Berliner, 2001). To date, formal state-implemented placement decision support algorithms include the Child and Adolescents Needs and Strengths (CANS) Algorithm (Lyons, 2009), the Children and Adolescent Service Intensity Instrument (CASII; Fallon et al., 2006), and the Child and Adolescent Functional Assessment Scale (CAFAS; Daleiden, Pang, Roberts, Slavin, & Pestle, 2010; Hodges, 1998).

Given the need to clarify the current state of out-of-home placement decision-making, this study aimed to (a) compare two models of placement decision-making used in the Illinois child welfare system and (b) characterize the state-level patterns of out-of-home placement decisions. Log-linear modeling was used to fit the observed distributions of out-of-home placements on the continuum of care by accounting for the two models described above and age-appropriate placements. The resulting analysis would thus illuminate recommended versus actualized placements and the degree of concordance (i.e., congruence) and discordance (i.e., incongruence) between the two models of placement decision-making. Although the placement settings and decision support mechanisms examined in this study might be perceived as local knowledge specific to the idiosyncrasies of a child welfare system, the findings have potential in clarifying the complexity of out-of-home placement decision-making in other practice settings.

Methods

Setting

As the state child welfare agency, the Illinois Department of Children and Family Services (IDCFS) aids out-of-home placement decision-making after a child enters the system by using a multidisciplinary team approach and a decision support algorithm for all placement types, in increasing level of restrictiveness: Independent Living Option (ILO), Transitional Living Program (TLP), Foster Care (FC), Specialized Foster Care (SFC), Group Home (GH), and Residential Treatment Center (RTC).

ILO refers to independent placements for older youth to acquire life skills that will facilitate community reintegration as these youth transition to adulthood (Kroner & Mares, 2009). TLP refers to small-scale group living arrangements that also provide skill-building to prepare youth for independence, though typically with greater level of supervision (HHS, 2006). FC refers to traditional kinship and non-kinship foster care placements in family settings (Winokur, Crawford, Longobardi, & Valentine, 2008). SFC refers to a higher level of foster care for children with greater behavioral, emotional, developmental or medical needs, and requires foster parents to receive specialized training and professional supervision that often leads to specialized foster licensure (Farmer, Wagner, Burns, & Richards, 2003). GH placements typically serve older youth whose needs exceed the capacity of foster care, and these placements are characterized by small-scale, shared living settings with variability in staffing, organizational style, and day-to-day programming (Breland-Noble, Farmer, Dubs, Potter, & Burns, 2005). RTC is the most restrictive setting for children and youth with severe behavioral and emotional disorders, limited community support systems, and risks for danger to self and others. RTCs are 24/7 institutions that vary in size, staffing, treatment modality, and organizational structure (James, Landsverk, Leslie, Slymen, & Zhang, 2008). Although this continuum of care is conceptualized for the Illinois child welfare system, similar continua of care that arrange placement types from the least to the most restrictive settings are quite common (Armour & Schwab, 2007; Duppong Hurley et al., 2009).

Child and Youth Investment Teams

Since July of 2005, IDCFS has implemented Child and Youth Investment Teams (CAYIT) to manage changes in out-of-home placements statewide (IDCFS, 2010). Every CAYIT consists of an intake coordinator, a reviewer, a facilitator, and an implementation coordinator. In addition, the CAYIT invites the child (if older than 12), caregivers, and other pertinent individuals to arrive at a consensual, informed placement recommendation. Typical triggers for CAYIT staffing include current placement becoming at risk, multiple placement changes in recent months, and a recognized need for a more restrictive level of care. The CAYIT proceeds with a discussion of the case and the reasons for a proposed placement change, followed by a clinical assessment using the CANS tool (Lyons, 2009) and formulation of a service plan and the most appropriate level of care. The implementation coordinator then uses the final recommendation to identify specific placement providers.

CANS Algorithm

During staffing, the CAYIT completes the CANS assessment based on the presenting clinical profile. The CAYIT CANS consists of 104 items. There are four anchored ratings per item to indicate the range of severity: “0” (No evidence and no need for action”), “1” (Need for watchful waiting), “2” (Need for action), and “3” (Need for immediate action). The ratings of “2” and “3” indicate actionable items that require associated service planning. Items are grouped into eight clinical domains: *Trauma Experiences, Traumatic Stress Symptoms, Strengths, Life Domain Functioning, Acculturation, Behavioral/Emotional Needs,*

Table 1
Operationalization of concordance and discordance.[a,b,c]

			CAYIT recommendation					
			Age ≥16 only			All ages		
		Level of care[d]	ILO	TLP	FC	SFC	GH	RTC
CANS Algorithm recommendation	Age ≥16 only	ILO	**C**	$D_{Over\ (+1)}$	$D_{Over\ (+2)}$	$D_{Over\ (+3)}$	$D_{Over\ (+4)}$	$D_{Over\ (+5)}$
		TLP	$D_{Under\ (-1)}$	**C**	$D_{Over\ (+1)}$	$D_{Over\ (+2)}$	$D_{Over\ (+3)}$	$D_{Over\ (+4)}$
	All ages	FC	$D_{Under\ (-2)}$	$D_{Under\ (-1)}$	**C**	$D_{Over\ (+1)}$	$D_{Over\ (+2)}$	$D_{Over\ (+3)}$
		SFC	$D_{Under\ (-3)}$	$D_{Under\ (-2)}$	$D_{Under\ (-1)}$	**C**	$D_{Over\ (+1)}$	$D_{Over\ (+2)}$
		GH	$D_{Under\ (-4)}$	$D_{Under\ (-3)}$	$D_{Under\ (-2)}$	$D_{Under\ (-1)}$	**C**	$D_{Over\ (+1)}$
		RTC	$D_{Under\ (-5)}$	$D_{Under\ (-4)}$	$D_{Under\ (-3)}$	$D_{Under\ (-2)}$	$D_{Under\ (-1)}$	**C**

[a] C = concordant; D = discordant; Under = under-placement; Over = over-placement.
[b] Subscript (number) = (degree of under-placement (−) or over-placement (+) compared to CANS Algorithm recommendations).
[c] Bold face indicates concordance between the CANS Algorithm and the CAYIT recommendations.
[d] ILO = Independent Living Option; TLP = Transitional Living Program; FC = Foster Care; SFC = Specialized Foster Care; GH = Group Home; RTC = Residential Treatment Center.

Risk Behaviors, and *Caregiver Needs and Strengths*. The *Strengths* items have reverse meanings, such that "0" indicates a centerpiece strength, and "3" indicates a strength not yet identified.

The CANS assessment is embedded across IDCFS programs to track clinical outcomes (Weiner, Schneider, & Lyons, 2009) and in child welfare systems in multiple states and international settings (Lyons, 2009). The CANS has demonstrated strong field reliability, audit reliability, and concurrent validity with the CAFAS (Anderson, Lyons, Giles, Price, & Estle, 2003; Lyons, 2004, 2009). The CANS also has established strong item-level inter-rater reliability among researchers and between researchers and clinicians, and it has achieved on average .81 for the former and .85 for the latter across CANS domains (Anderson et al., 2003). Specifically, every rater of the CANS, including the CAYIT team members, must have at least a bachelor's degree to complete a CANS training using case vignettes or case records and obtain annual re-certification to meet at least a reliability of .70 using an intra-class correlation coefficient. As of 2009, there were more than 30,000 trained and certified CANS users (Lyons, 2009). Across assessment contexts, trained CANS users have an average reliability of .80 post-training with vignettes, .85 with case records, and .90 with live interviewers, based on the CANS training database (Lyons, 2009; The Praed Foundation, 2010). Thus, these CANS reliability standards would minimize any inter-rater variability between different CAYIT teams, and any observed variability would be error by chance rather than discrepancies in between-team reliability.

To facilitate the CAYIT's informed placement decision-making, IDCFS also implemented the CANS Algorithm, which uses select items from the completed CANS profile and Boolean logic to generate a placement recommendation (Lyons, 2004; Weiner et al., 2009). Focus groups comprising IDCFS policymakers, community providers, clinicians, and mental health services researchers developed the level-of-care criteria with corresponding CANS items and rating thresholds. The CANS Algorithm has field validity, as variations of the CANS Algorithm have been applied by the Philadelphia Department of Human Services and Alaska Youth Initiative (Lyons, 2004). The Illinois CANS Algorithm has different placement criteria specific to each of the six care levels described above, using different combinations of items and ratings from different domains. During the CAYIT staffing, with a completed CANS profile, the CANS Algorithm recommendation is made available for the CAYIT to consider and to inform a final recommendation.

Operationalizing concordance and discordance (over-placement and under-placement)

Given the two placement decision-making models, a logical way to examine placement decision patterns is to compare the models regarding concordance (i.e., same decisions) and discordance (i.e., different decisions) across the six possible levels of care. There is, however, limited a priori guidance on comparing concordant and discordant placement decisions, other than placement of alcohol treatment options (Magura et al., 2003). Thus, concordance and discordance were operationalized in the most comprehensive way. First, concordance meant that both the CAYIT and the CANS Algorithm recommended the same level of care. Second, discordance was divided into over-placement versus under-placement with respect to the CANS Algorithm recommendation, based on the difference in restrictiveness on the continuum of care and the degree of discordance (e.g., three-level versus one-level over-placement or under-placement). Further, different ranges of placement options for children below age 16 and for youth above age 16 were considered, as only the latter group qualifies for TLP and ILO settings.

Table 1 shows all the possible concordant and discordant decisions for the two age groups. Concordant levels of care are on the diagonals, discordant levels of care are off-diagonal (over-placement is above the diagonal and under-placement is below the diagonal), and the degree of discordance is represented by the distance a discordant level of care is from the diagonal. Note that recommendations by the CAYIT also represent actual placements, as the CANS Algorithm is an advisory tool. For children below age 16, there are four levels of care and therefore four concordant combinations possible and 12 discordant combinations (six over-placements and the six under-placements). For youth aged 16 or above, there are six

Table 2
Distribution of CANS algorithm and CAYIT recommendations for children younger than age 16.[a]

	Level of care[b]	CAYIT recommendation				Total
		FC	SFC	GH	RTC	
CANS Algorithm recommendation	FC	**798 (20.4%)**	478 (12.2%)	36 (0.9%)	34 (0.9%)	1346 (34.4%)
	SFC	212 (5.4%)	**632 (16.2%)**	43 (1.1%)	99 (2.5%)	986 (25.2%)
	GH	31 (0.8%)	104 (2.7%)	**31 (0.8%)**	71 (1.8%)	237 (6.1%)
	RTC	116 (3.0%)	414 (10.6%)	94 (2.4%)	**718 (18.5%)**	1342 (34.3%)
	Total	1157 (29.6%)	1628 (41.6%)	204 (5.2%)	922 (23.6%)	3911 (100.0%)

[a] Bold face indicates concordance between the CANS Algorithm and the CAYIT recommendations.
[b] FC = Foster Care; SFC = Specialized Foster Care; GH = Group Home; RTC = Residential Treatment Center.

levels of care and therefore six concordant combinations possible and 30 discordant combinations (15 over-placements and 15 under-placements).

Sample

All children and youth receiving CAYIT assessment after July 1, 2005, were eligible for the study. Overall, 7816 (60.8%) of the 12,849 CAYIT assessments from July 1, 2005, to April 29, 2010, which represented 6096 unique children and youth, were included. All of these children and youth met the following study eligibility criteria:

1. CAYIT recommended placements occurred within six months following staffing. This accounted for wait time needed for placements to be implemented since placement changes do not take place immediately.
2. CAYIT level of care recommendation was the same as the actual subsequent placement. Excluded cases might arise due to post-decision events that render the CAYIT decision impossible. For example, following a CAYIT staffing, a child might run away. If external events interfere, the original CAYIT recommendation could not be implemented, so the case would not be germane to this study. Also, placements not made by the intent of IDCFS (e.g., detention centers, shelters, unknown placements) were not considered.
3. CAYIT assessments that occurred after a CAYIT assessment with the same recommendation were excluded. Generally, these CAYIT assessments are connected to identify and correct the failure to place a child.
4. Multiple CAYIT assessments for the same child were included as long as the prior criteria were met.

The study's sample indicates an even breakdown of children below age 16 (49.96%) and youth at or above age 16 (50.04%) and a slightly greater proportion of males (52.2%). The overall ethnic composition of the sample was as follows: 66.9% African American; 26.8% Caucasian; 5.0% Hispanic, Native American, or Asian; and 1.3% unknown.

Data analysis

Log-linear modeling was used to identify concordant and discordant placements that contributed the most effects statistically to the observed placement distributions. Age ranges relevant to placement criteria and placement options were also counted for: 0–7 years old, 8–15 years old, and ≥16 years old. Thus, by IDCFS policy, there are three exogenous factors that affect the distributions of out-of-home placement in the Illinois child welfare system: (a) age, (b) CANS Algorithm recommendation, and (c) CAYIT recommendation.

Log-linear modeling examines associations in a multidimensional crosstabulation of the categorical levels of interest, including main and interaction effects, to identify the most parsimonious model that accounts for observed cell frequencies (Christensen, 1997), especially in higher-order contingency tabulations involving more than two factors (Elliot, 1988). To construct the log-linear model for this study, structural zeros were imposed to signify impossible outcomes such that their expected frequency were zero, namely children below age 16 getting placed in ILO or TLP and children below age seven getting placed in GH and RTC. In this study, a saturated three-way model would, by definition, be the best fit to account for all possible effects and the observed cell distributions in Tables 2 and 3. However, a saturated model is considered trivial and nonparsimonious when a lower-order model can produce a comparable fit that still explains the observed data with equally meaningful interpretations (Christensen, 1997). Through backward estimation, we began with the saturated model until we arrived at the most parsimonious, lower-order, nonsaturated model.

Results

Descriptive distributions of CANS Algorithm and CAYIT recommendations

Tables 2 and 3 delineate concordance and discordance between the CANS Algorithm and the CAYIT recommendations by level of care, separately by age group. Overall, 3627 (46.4%) CAYIT recommendations were concordant with the CANS Algorithm, 2828 (36.2%) under-placed, and 1361 (17.4%) over-placed. The degree of discordance tended to be small, within a

Table 3
Distribution of CANS Algorithm and CAYIT recommendations for youth at age 16 or above.[a]

	Level of care [b]	CAYIT recommendation						
		ILO	TLP	FC	SFC	GH	RTC	Total
CANS Algorithm recommendation	ILO	**314 (8.0%)**	35 (0.9%)	15 (0.4%)	6 (0.2%)	–	–	370 (9.5%)
	TLP	110 (2.8%)	**257 (6.6%)**	44 (1.1%)	58 (1.5%)	30 (0.8%)	8 (0.2%)	507 (13.0%)
	FC	237 (6.1%)	273 (7.0%)	**288 (7.4%)**	178 (4.6%)	54 (1.4%)	19 (0.5%)	1049 (26.9%)
	SFC	38 (1.0%)	141 (3.6%)	79 (2.0%)	**129 (3.3%)**	51 (1.3%)	40 (1.0%)	478 (12.2%)
	GH	44 (1.1%)	181 (4.6%)	61 (1.6%)	90 (2.3%)	**61 (1.6%)**	62 (1.6%)	499 (12.8%)
	RTC	25 (0.6%)	196 (5.0%)	90 (2.3%)	151 (3.9%)	141 (3.6%)	**399 (10.2%)**	1002 (25.7%)
	Total	768 (19.7%)	1083 (27.7%)	577 (14.8%)	612 (15.7%)	337 (8.6%)	528 (13.5%)	3905 (100.0%)

[a] Bold face indicates concordance between the CANS Algorithm and the CAYIT recommendations.
[b] ILO = Independent Living Option; TLP = Transitional Living Program; FC = Foster Care; SFC = Specialized Foster Care; GH = Group Home; RTC = Residential Treatment Center.

one-level (26.4%) or two-level (17.1%) difference. Concordance was more common among children younger than 16 (55.7%) than their older counterparts (37.1%).

In the younger age group, Table 3 shows that concordance was highest in the least and most restrictive settings, FC (20.4%) and RTC (18.4%), respectively. One-level under-placement mainly occurred in FC (5.4%), and two-level under-placement exclusively in SFC (10.6%). One-level over-placement populated primarily in SFC (12.2%). The CAYIT tended to recommend SFC (41.6%), FC (29.6%), and RTC (23.6%). The CANS Algorithm tended to recommend RTC (34.5%), FC (34.4%), and SFC (25.2%). Table 4 shows that concordance in the older age group was also highest on the two ends of the continuum of care, RTC (10.2%) and ILO (8.0%), followed by TLP (6.6%). One-level under-placement occurred mostly in TLP (7.0%), and two-level under-placement in ILO (6.1%). One-level over-placement tended to occur in SFC (4.6%). Overall, the CAYIT tended to recommend and place youth in TLP (27.8%) and ILO (19.7%), followed by SFC (15.7%), FC (14.8%), and RTC (13.5%). The CANS Algorithm, however, tended to recommend FC (26.9%) and RTC (25.7%), followed by TLP (13.0%), GH (12.8%), and SFC (12.2%).

Predicting patterns of CANS Algorithm and CAYIT recommendations

To augment the descriptive distributions of the level-of-care recommendations, log-linear analysis pinpointed how the observed distributions could be predicted by the three policy-justified factors that directly influence out-of-home placement distributions in Illinois: (a) child's age, (b) CANS Algorithm recommendation, and (c) CAYIT recommendation. When organized by these factors on a contingency table (not shown), 43 structural zeros were deemed appropriate. Based on the three factors, the saturated model had one three-way effect (i.e., saturated model), three two-way effects (i.e., second-order interactions), and three one-way effects (i.e., main effect model).

As shown in Table 4, starting from the saturated model, we used hierarchical log-linear modeling through backward estimation to find the best-fitting model to represent the observed data. Based on the Bayesian information criterion (BIC), the second order model (df = 49, BIC = 641.3), which includes the three second order interactions and the three main effects, produced the best-fitting and interpretable model that is comparable to the saturated model (df = 64, BIC = 653.5). Although the goodness-of-fit χ^2 (8119.5) compared to the saturated model χ^2 (8169.9) was statistically significant (χ^2 difference = 50.4, $p < .001$), the second-order model still provided a comparatively better fit than the other lower-order models, in which goodness-of-fit χ^2 and BIC deviated greatly from the saturated model.

This equation summarizes the second-order log-linear model:

$$\ln(\mathrm{Freq}_{ijk}) = \mu + \left[\lambda_i^{(\mathrm{Age})} + \lambda_j^{(\mathrm{CAYIT})}\right] + \left[\lambda_{ij}^{(\mathrm{Age}\times\mathrm{CANS})} + \lambda_{ik}^{(\mathrm{Age}\times\mathrm{CAYIT})} + \lambda_{jk}^{(\mathrm{CANS}\times\mathrm{CAYIT})}\right]$$

where the natural log of the frequency any cell on the three-factor contingency table equals the sum of the grand mean (μ) or the constant, the three first-order estimates, $\lambda_i^{(\mathrm{Age})}$, $\lambda_j^{(\mathrm{CAYIT})}$, and $\lambda_k^{(\mathrm{CAYIT})}$, and the three second-order estimates, $\lambda_{ij}^{(\mathrm{Age}\times\mathrm{CANS})}$, $\lambda_{ik}^{(\mathrm{Age}\times\mathrm{CAYIT})}$, and $\lambda_{jk}^{(\mathrm{CANS}\times\mathrm{CAYIT})}$.

Table 5 presents results from the log-linear analysis using effect coding on the three categorical factors. The more significantly positive a parameter estimate for a particular effect, the more cases were predicted to be in that particular cell above and beyond those predicted by the constant and other effects expected by chance. Conversely, the more negative a parameter estimate, if significant, the fewer cases are predicted in that particular cell. Parameter estimates are the differences from the grand mean of all level of the corresponding factor or interacting factors.

Main effects: age, CANS Algorithm, and CAYIT recommendations

The age effect on placement distributions was most salient among children aged 8–15 ($\lambda = 1.6$, $p < .001$) and children aged 16 or above ($\lambda = 1.2$, $p < .001$), compared to children aged below 7 years old. This suggests that there is a high level of placement needs among children aged 8 or above.

Table 4
Model comparisons based on the three factors: (1) Age, (2) CANS Algorithm recommendation, and (3) CAYIT recommendation.[a]

		Model								
		First-order only (main effects only)	First-order + (Age × CANS Algorithm)	First-order + (Age × CAYIT)	First-order + (CANS Algorithm × CAYIT)	First-order + (Age × CAYIT) + (CANS Algorithm × CAYIT)	First-order + (Age × CANS Algorithm) + (CANS Algorithm × CAYIT)	First-order + (Age × CANS Algorithm) + (Age × CAYIT)	Second-order only (main effects and two-way interactions only)	Saturated model
Model statistics	χ^2	3314.1	4009.4	4083.0	7141.9	7912.9	7723.9	4711.8	**8119.5**	8169.9
	df	12	18	18	37	43	43	24	**49**	64
Goodness-of-fit	χ^2	4835.7	4160.4	4086.8	1027.9	257.0	446.0	3458.1	**50.4**	0
	BIC	5272.2	4622.0	4548.4	1568.8	822.9	1.011.8	3944.6	**641.3**	653.5

[a] Bold face indicates best-fitting model.

Table 5
Log-linear analysis of the second-order model of the three factors: (1) Age, (2) CANS Algorithm recommendation, and (3) CAYIT recommendation.

Parameter	Parameter estimates				
	Estimate	Standard error	z	p	Confidence interval
Age					
8–15	1.6	0.1	11.9	***	(1.3, 1.8)
≥16	1.2	0.1	8.7	***	(0.9, 1.4)
Reference: 0–7					
CANS Algorithm recommendation[a]					
ILO	−3.5	0.4	−8.3	***	(−4.3, −2.7)
TLP	−0.2	0.2	−1.5	.13	(−0.5, 0.1)
SFC	1.2	0.1	9.8	***	(0.9, 1.4)
GH	−0.7	0.1	−4.6	***	(−0.9, −0.4)
RTC	1.3	0.1	10.5	***	(1.1, 1.5)
Reference: FC					
CAYIT recommendation[a]					
ILO	0.7	0.1	5.8	***	(0.5, 1.0)
TLP	1.9	0.1	17.1	***	(1.7, 2.1)
SFC	1.7	0.2	8.9	***	(1.3, 2.1)
GH	−3.1	0.5	−6.6	***	(−4.0, −2.2)
RTC	−2.3	0.3	−6.7	***	(−3.0, −1.6)
Reference: FC					
(Age) × (CANS Algorithm recommendation)[a]					
(Age: 8–15) & (SFC)	−0.1	0.1	−1.3	.18	(−0.2, 0.05)
(Age: 8–15) & (GH)	−0.0	0.1	−0.2	.81	(−0.3, 0.2)
(Age: 8–15) & (RTC)	0.3	0.1	3.8	***	(0.1, 0.4)
(Age: ≥ 16) & (SFC)	−0.9	0.1	−10.1	***	(−1.0, −0.7)
(Age: ≥ 16) & (GH)	1.1	0.1	9.4	***	(0.9, 1.4)
(Age: ≥ 16) & (RTC)	0.2	0.1	2.4	*	(0.0, 0.4)
Reference: (Age: 0–7) & (FC)					
(Age) × (CAYIT recommendation)[a]					
(Age: 8–15) & (SFC)	−0.6	0.1	−4.7	***	(−0.9, −0.4)
(Age: 8–15) & (GH)	0.5	0.4	1.2	.22	(−0.3, 1.2)
(Age: 8–15) & (RTC)	1.1	0.2	6.6	***	(0.8, 1.5)
(Age: ≥16) & (SFC)	−1.3	0.1	−9.5	***	(−1.6, −1.1)
(Age: ≥16) & (GH)	1.7	0.4	4.7	***	(1.0, 2.5)
(Age: ≥16) & (RTC)	0.5	0.2	2.8	**	(0.1, 0.8)
Reference: (Age: 0–7) & (FC)					
(CANS Algorithm recommendation) × (CAYIT recommendation)[a]					
Concordance					
(ILO) & (ILO)	6.1	0.4	14.1	***	(5.2, 6.9)
(TLP) & (TLP)	1.3	0.2	6.9	***	(0.9, 1.6)
(SFC) & (SFC)	1.1	0.2	6.2	***	(0.7, 1.4)
(GH) & (GH)	1.2	0.3	3.5	***	(0.5, 1.8)
(RTC) & (RTC)	4.1	0.3	13.1	***	(3.5, 4.8)
Discordance: under-placement[b]					
−1: (TLP) & (ILO)	0.7	0.2	3.4	***	(0.3, 1.2)
−1: (GH) & (SFC)	−0.4	0.2	−0.2	.82	(−0.4, 0.3)
−1: (RTC) & (GH)	1.6	0.3	5.0	***	(1.0, 2.2)
−2: (SFC) & (TLP)	−0.5	0.2	−2.6	**	(−0.8, −0.1)
−2: (RTC) & (SFC)	0.2	0.2	1.3	.19	(−0.1, 0.6)
−3: (SFC) & (ILO)	−1.9	0.3	−7.2	***	(−2.4, −1.4)
−3: (GH) & (TLP)	−0.1	0.2	−0.8	.44	(−0.5, 0.2)
−4: (GH) & (ILO)	−1.8	0.3	−7.0	***	(−2.2, −1.3)
−4: (RTC) & (TLP)	−1.0	0.2	−6.1	***	(−1.3, −0.7)
−5: (RTC) & (ILO)	−3.9	0.3	−12.9	***	(−4.5, −3.3)
Discordance: over-placement[b]					
+1: (ILO) & (TLP)	0.6	0.5	1.2	.23	(−0.4, 1.5)
+1: (SFC) & (GH)	0.7	0.3	2.0	*	(0.1, 1.3)
+1: (GH) & (RTC)	1.7	0.3	5.0	***	(1.0, 2.3)
+2: (TLP) & (SFC)	−0.2	0.3	−0.6	.56	(−0.7, 0.4)
+2: (SFC) & (RTC)	0.7	0.3	2.1	*	(0.1, 1.4)
+3: (ILO) & (SFC)	−1.2	0.7	−1.8	.08	(−2.5, 0.1)
+3: (TLP) & (GH)	0.3	0.4	0.7	.49	(−0.5, 1.1)
+4: (ILO) & (GH)	−3.4	1.4	−2.4	*	(−6.1, −0.6)
+4: (TLP) & (RTC)	−1.7	0.6	−3.1	**	(−2.8, −0.6)
+5: (ILO) & (RTC)	−2.9	1.4	−2.0	*	(−5.7, −0.1)

Table 5 (*Continued*)

Parameter	Parameter estimates				
	Estimate	Standard error	z	p	Confidence interval
Reference: (FC) & (FC)					
Constant	3.5	0.1	44.6	***	(3.4, 3.7)

[a] ILO = Independent Living Option; TLP = Transitional Living Program; SFC = Specialized Foster Care; GH = Group Home; RTC = Residential Treatment Center.
[b] "−1" denotes one level of care under-placed compared to the CANS Algorithm, "−2" denotes two levels of care under-placed, and so on; "+1" denotes one level of care over-placed, "+2" denotes two levels of care over-placed, and so on.
[*] $p < .05$;.
[**] $p < .01$;.
[***] $p < .001$.

Compared to the CANS Algorithm's recommendation of FC, all other levels of care except for TLP contributed significantly to the observed distributions, either above or below expected by chance. Specifically, positive effects included recommendations for RTC ($\lambda = 1.3$, $p < .001$) and SFC ($\lambda = 1.2$, $p < .001$). Recommendations for ILO ($\lambda = -3.5$, $p < .001$) and GH ($\lambda = -0.7$, $p < .001$), on the other hand, reduced the predicted counts.

Compared to the CAYIT's recommendation of FC, all levels of care yielded significant effects. Specifically, the CAYIT's recommendations for TLP ($\lambda = 1.9$, $p < .001$), SFC ($\lambda = 1.7$, $p < .001$), and ILO ($\lambda = 0.7$, $p < .001$) had significantly positive effects. Recommendations for the most restrictive settings, GH ($\lambda = -3.1$, $p < .001$) and RTC ($\lambda = -2.3$, $p < .001$), however, reduced the predicted counts.

Second order effects: Age × CANS Algorithm, Age × CAYIT, CANS Algorithm × CAYIT

The log-linear model produced four significant parameter estimates for the age × CANS Algorithm association: three positive associations for children aged 16 or above recommended for GH ($\lambda = 1.1$, $p < .001$) and for RTC ($\lambda = 0.2$, $p < .05$) and for children aged 8–15 recommended for RTC ($\lambda = 0.3$, $p < .001$) and a negative association for children aged 16 or above recommended for SFC ($\lambda = -0.9$, $p < .001$).

There were five significant effects for the Age × CAYIT association. Similar to the Age × CANS Algorithm associations, there were positive associations for children aged 16 or above recommended for GH ($\lambda = 1.7$, $p < .001$) and for RTC ($\lambda = 0.5$, $p < .01$), though there was a negative association for the same age group recommended for SFC ($\lambda = -1.3$, $p < .001$). For children aged eight to 15 recommended for RTC, the association effect was positive ($\lambda = 1.1$, $p < .001$), though the association effect was negative for those recommended for SFC ($\lambda = -0.6$, $p < .001$).

The focus of our study is on the CANS Algorithm × CAYIT association. From here on the form "X–Y" will denote the pairing of "CANS Algorithm recommended level of care X and the CAYIT recommended level of care Y." Further, providing concordant and discordant parameter estimates with odds ratios (ORs) can facilitate interpretation in terms of effect size. All concordant parameter estimates, compared to the reference group FC-FC, were statistically significant in the positive direction and strongest on the two ends of the continuum, in this descending order: ILO-ILO ($\lambda = 6.1$, $OR = 442.0$, $p < .001$), RTC-RTC ($\lambda = 4.1$, $OR = 62.9$, $p < .001$), TLP-TLP ($\lambda = 1.3$, $OR = 3.6$, $p < .001$), GH-GH ($\lambda = 1.2$, $OR = 3.2$, $p < .001$), and SFC-SFC ($\lambda = 1.1$, $OR = 2.9$, $p < .001$).

Discordance had greater variability. Positive and significant parameter estimates mainly occurred in one-level under-placement, RTC-GH ($\lambda = 1.6$, $OR = 4.8$, $p < .001$) and TLP-ILO ($\lambda = 0.8$, $OR = 2.2$, $p < .001$), and one-level over-placement, GH-RTC ($\lambda = 1.7$, $OR = 5.3$, $p < .001$) and SFC-GH ($\lambda = 0.7$, $OR = 1.9$, $p < .05$). The lone significant two-level over-placement was SFC-RTC ($\lambda = 0.7$, $OR = 2.0$, $p < .05$). Higher levels of under-placement and over-placement consistently produced negative associations.

Discussion

This study characterized the patterns of out-of-home placement decision-making and actual placements made in the Illinois child welfare system by comparing placement recommendations made by the multidisciplinary CAYIT and recommendations by the CANS Algorithm. Several key implications emerge. First, concordance (i.e., agreement between the two models of decision-making) was more attainable for younger children than for older youth. This might reflect the increasing flexibility of placing older youth due to a wider range of available placement options than for younger children where foster home is typically the de facto placement of choice.

Second, all other factors being equal, log-linear analysis revealed the divergent and informative patterns of placement decision-making between the CANS Algorithm and the CAYIT. With the CANS Algorithm, relative to the recommendation for foster care, there was greater propensity toward recommendations of specialized foster care and residential settings, though independent living options were extremely unlikely. Since the CANS Algorithm is heavily driven by clinical complexity, this pattern of recommendations seems to align with the algorithm's sensitivity to behavioral and emotional profiles. On the contrary, the CAYIT was least likely to recommend the most restrictive group home and residential settings, while leaning toward community-based settings such as transitional living programs and specialized foster care. These findings are consistent with state placement policies to enable lower level of care settings to treat the more severely disturbed children and youth, provided the necessary services are available (Los Angeles County Department of Children and Family Services, 2009; Wisconsin Department of Children & Families, 2011a;Wisconsin Department of Children & Families, 2011b). Considering the intensity of service can vary independent of the restrictiveness of the setting, decision-makers have greater flexibility to justify least restrictive recommendations that are contingent upon the needs of the children and youth being met.

Third, with each decision-making model, a child's age played a different role in the patterns of placement recommendations made. For the CANS Algorithm, the propensity toward a recommendation for residential setting was bolstered by age above eight years. This also reinforces the relative immutability of the CANS Algorithm in the face of clinical complexity, even for younger children who might not be ready for residential settings. For the CAYIT, there was an overall unlikelihood of recommending residential care, which saved the youngest age group from entering institutional settings. In practice, it seems that a higher age threshold for residential placement might benefit children by providing more opportunities and time to stabilize in the community if the services needed are available. The same can be said for group home. However, a related effect was that the youngest age group was more likely found in specialized foster care. The independent trends of the two decision-making models and their interacting trends with a child's age highlight the strengths and sensitivity unique to each model. In the context of this study, team decision-makers seem to embrace the principle of least restrictive setting in practice more readily than a decision support algorithm, where such capacity is to be seen in the face of complex clinical ratings.

Important lessons can be learned from agreement and disagreement between the two models. Log-linear analysis clarified overall concordance was strongest in the least restrictive setting of independent living options and foster care, and in the most restrictive setting of residential care. One explanation is that children and youth in these concordant groups stand out clinically and functionally, which facilitates decision-making. For instance, a child or youth with serious emotional and behavioral disturbance is likely to be "red-flagged" by team decision-makers and by the clinical rating-based algorithm. Alternatively, a child or youth with significant strengths and coping skills is a likely candidate for the least restrictive setting where the strengths and skills can be maintained and strengthened. Lesser odds of concordance in mid-range placements such as specialized foster care and group home might also carry important implications. Perhaps the fit between a child's need and an appropriate level of care around these placements is less clear than it is at the extremes.

Although attaining and maintaining concordance is important and validates the merits of either decision-making model, understanding discordance or disagreement between the two models is critical to improving children and youth's out-of-home placement experience. Descriptively, results found that, relative to the CANS Algorithm recommendations, discordance either in terms of under-placement or over-placement occurred between adjacent levels of care (e.g., foster care and specialized foster care) as opposed to between two ends of the continuum of care (e.g., independent living option and residential treatment center). This suggests that the margin of difference in decision-making between the two models is reasonably small, which was confirmed with the log-linear analysis showing greater odds of under- or over-placement by one level than higher levels of discordance. The clusters of discordance with higher odds deserve greater attention because these are likely the placement scenarios where ambiguity ensues, given the different yet not too different recommendations by the algorithm. Since concordance and discordance is founded on one decision model relative to another, it is important to re-emphasize that the CANS Algorithm is intended as a decision support, rather than an expert replacement system. This study documents this distinction to allow the flexibility of decision-making beyond a recommended placement.

This study could potentially serve as an impetus for future research based on the diverse patterns of placement decisions made. First, given the large effect sizes associated with concordant decisions, how these patterns predict child welfare outcomes such as clinical functioning and placement stability over time would tremendously benefit the field, from guiding caseworker's discretion when they receive and follow a case to informing child welfare policy changes (e.g., incorporating a decision support algorithm). Pilot outcome data in residential treatment centers that favor concordant decisions over discordant decisions offer promising leads to other placement types (Chor et al., 2012). Second, evidence-based placement decision-making and evidence-based service planning should co-occur. By clarifying the trajectory of out-of-home placement decision-making after a child enters state custody, this will help synchronize and calibrate corresponding services that the child needs. Further, qualitative research can provide a better understanding of the child's perspective and how it might influence the placement decision-making process. There is potential in quality improvement by re-examining discordant cases and their rationale to inform future decision-making. A corresponding effort in qualitative data collection is needed to provide a comprehensive analysis of concordant versus discordant decision-making. Similarly, although this study examined the end results of the placement decisions made, there is much to learn about the process of decision-making that produces a final decision. Finally, how decision-makers utilize a placement decision support algorithm (e.g., As an advisory tool? When to override an algorithm?) in practice will enhance the development of feasible and generalizable algorithms. Further, the overall discordant trends on a state-level such as in Illinois offer learning opportunities for quality assurance, as a review of samples discordant cases can help infer the "gold standard" of placement decision-making. Discordant cases also provide potential lessons for quality improvement through monitoring of placement decisions that might prove problematic from the perspective of the decision-makers, the child, or placement providers.

There are several limitations to this study. First, since we did not account for the child's placement of origin at the time of the CAYIT staffing, subsequent concordance and discordance lacks a frame of reference based on the preceding placement. For instance, discordance resulting from a step-up from the current placement might have vastly different implications than from a step-down or from a lateral move. Second, while the main exogenous factors that are inherent in the Illinois child welfare system – child's age, the CAYIT and the CANS Algorithm recommendations – address both individual-case and systemic factors of the Decision-Making Ecology Framework (Baumann et al., 2011), there are by no means comprehensive as there are other potentially informative variables predicting concordance and discordance. For instance, state regions may vary regarding placement availability (e.g., urban vs. rural). Although based on our operationalization, children and youth who were under-placed had clinically severe baseline, certain case-mixes (e.g., sexual aggression or psychosis profile) that may predispose to particular levels of care were not explored. Third, we did not examine or compare with the patterns of placement decision-making prior to the implementation of the CAYIT and the CANS Algorithm. Hence, it remains unclear whether the observed patterns reflected the effectiveness of implementation or conceivable changes from pre-existing practice. Other limitations pertain to the lack of associated outcome or placement stability data, which are necessary to ascertain the benefits of concordant decisions and the disadvantages of discordant decisions. Further, we did not account for the variability in how the CANS Algorithm was used by the CAYIT and confounding factors such as placement availability and child's preference that might contribute to the final placement decision. Despite these limitations, the current study provides a first glimpse into the role of innovative placement decision-making in a large child welfare system.

References

Aarons, G. A., James, S., Monn, A. R., Raghavan, R., Wells, R. S., & Leslie, L. K. (2010). Behavior problems and placement change in a national child welfare sample: A prospective study. *Journal of the American Academy of Child and Adolescent Psychiatry*, *49*, 70–80.

Anderson, R. L., Lyons, J. S., Giles, D. M., Price, J. A., & Estle, G. (2003). Reliability of the Child and Adolescent Needs and Strengths-Mental Health (CANS-MH) Scale. *Journal of Child and Family Studies*, *12*, 279–289. http://dx.doi.org/10.1023/a:1023935726541

Arizona Department of Health Services, Division of Behavioral Health Services. (2009). *DBHS practice protocol: Child and family team practice*. Phoenix: Author. Retrieved from. http://www.azdh.gov

Armour, M. P., & Schwab, J. (2007). Characteristics of difficult-to-place youth in state custody: A profile of the Exceptional Care Pilot Project population. *Child Welfare*, *86*(3), 71–96.

Barth, R. P., Lloyd, E. C., Green, R. L., James, S., Leslie, L. K., & Landsverk, J. (2007). Predictors of placement moves among children with and without emotional and behavioral disorders. *Journal of Emotional and Behavioral Disorders*, *15*, 46–55. http://dx.doi.org/10.1177/10634266070150010501

Baumann, D. J., Dalgleish, L., Fluke, J., & Kern, H. (2011). *The decision-making ecology*. Washington, DC: American Humane Association.

Benbenishty, R., & Chen, W. (2003). Decision making by the child protection team of a medical center. *Health & Social Work*, *28*, 284–292.

Berger, L. M., Bruch, S. K., Johnson, E. I., James, S., & Rubin, D. (2009). Estimating the "impact" of out-of-home placement on child well-being: Approaching the problem of selection bias. *Child Development*, *80*, 1856–1876. http://dx.doi.org/10.1111/j.1467-8624.2009.01372.x

Bickman, L., Karver, M. S., & Schut, L. J. (1997). Clinician reliability and accuracy in judging appropriate level of care. *Journal of Consulting and Clinical Psychology*, *65*, 515–520.

Blakey, J. M., Leathers, S. J., Lawler, M., Washington, T., Natschke, C., Strand, T., & Walton, Q. (2012). A review of how states are addressing placement stability. *Children and Youth Services Review*, *34*, 369–378. http://dx.doi.org/10.1016/j.childyouth.2011.11.007

Breland-Noble, A. M., Farmer, E. M. Z., Dubs, M. S., Potter, E., & Burns, B. J. (2005). Mental health and other service use by youth in therapeutic foster care and group homes. *Journal of Child and Family Studies*, *14*, 167–180. http://dx.doi.org/10.1007/s10826-005-5045-5

Chor, K. H. B., McClelland, G. M., Weiner, D. A., Jordan, N., & Lyons, J. S. (2012). Predicting outcomes of children in residential treatment: A comparison of a decision support algorithm and a multidisciplinary team decision model. *Children and Youth Services Review*, *34*, 2345–2352. http://dx.doi.org/10.1016/j.childyouth.2012.08.016

Christensen, R. (1997). *Log-linear models and logistic regression*. New York, NY: Springer-Verlag.

Crampton, D. S., Crea, T. M., Abramson-Madden, A., & Usher, C. L. (2008). Challenges of street-level child welfare reform and technology transfer: The case of team decisionmaking. *Families in Society: Journal of Contemporary Social Services*, *89*, 512–520. http://dx.doi.org/10.1606/1044-3894.3823

Crea, T. M., Usher, C. L., & Wildfire, J. B. (2009). Implementation fidelity of team decisionmaking. *Children and Youth Services Review*, *31*, 119–124. http://dx.doi.org/10.1016/j.childyouth.2008.06.005

Daleiden, E. (2004). *Child status measurement: Operating characteristics of the CALOCUS and CAFAS*. Honolulu: State of Hawaii Department of Health Child and Adolescent Mental Health Division. Retrieved from http://hawaii.gov/health/mentalhealth/camhd/library/pdf/rpteval/mr/mr001.pdf

Daleiden, E., Pang, D., Roberts, D., Slavin, L., & Pestle, S. (2010). Intensive home-based services within a comprehensive system of care for youth. *Journal of Child and Family Studies*, *19*, 318–325. http://dx.doi.org/10.1007/s10826-009-9300-z

DeMuro, P., & Rideout, P. (2002). *Family to family tools for rebuilding foster care. Team decisionmaking involving the family and community in child welfare decisions part two: Building community partnership in child welfare*. Baltimore, MD: The Annie E. Casey Foundation.

Doran, L., & Berliner, L. (2001). *Placement decisions for children in long-term foster care: Innovative practices and literature review*. Olympia: Washington State Institute for Public Policy.

Duppong Hurley, K., Trout, A., Chmelka, M. B., Burns, B. J., Epstein, M. H., Thompson, R. W., & Daly, D. L. (2009). The changing mental health needs of youth admitted to residential group home care. *Journal of Emotional and Behavioral Disorders*, *17*, 164–176. http://dx.doi.org/10.1177/1063426608330791

Durbin, J., Cochrane, J., Goering, P., & Macfarlane, D. (2001). Needs-based planning: Evaluation of a level-of-care planning model. *Journal of Behavioral Health Services & Research*, *28*, 67–80.

Elliot, G. C. (1988). Interpreting higher order interactions in log-linear analysis. *Psychological Bulletin*, *103*, 121–130. http://dx.doi.org/10.1037/0033-2909.103.1.121

Fallon, T., Pumariega, A., Sowers, W., Klaehn, R., Huffine, C., Vaughan, T., & Grimes, K. (2006). A level of care instrument for children's systems of care: Construction, reliability and validity. *Journal of Child and Family Studies*, *15*, 140–152. http://dx.doi.org/10.1007/s10826-005-9012-y

Farmer, E. M. Z, Wagner, H. R., Burns, B. J., & Richards, J. T. (2003). Treatment foster care in a system of care: Sequences and correlates of residential placements. *Journal of Child and Family Studies*, *12*, 11–25. http://dx.doi.org/10.1023/a:1021349907744

Fisher, P. A., & Chamberlain, P. (2000). Multidimensional Treatment Foster Care: A program for intensive parenting, family support, and skill building. *Journal of Emotional and Behavioral Disorders*, *8*(3), 155–164. http://dx.doi.org/10.1177/106342660000800303

Fluke, J. D., Chabot, M., Fallon, B., MacLaurin, B., & Blackstock, C. (2010). Placement decisions and disparities among aboriginal groups: An application of the decision making ecology through multi-level analysis. *Child Abuse & Neglect*, *34*(1), 57–69. http://dx.doi.org/10.1016/j.chiabu.2009.08.009

Frost, N., & Robinson, M. (2007). Joining up children's services: Safeguarding children in multi-disciplinary teams. *Child Abuse Review*, *16*(3), 184–199, doi: 10.1002/car.967.

Griffin, G., Martinovich, Z., Gawron, T., & Lyons, J. S. (2009). Strengths moderate the impact of trauma on risk behaviors in child welfare. *Residential Treatment for Children & Youth*, *26*(2), 105–118. http://dx.doi.org/10.1080/08865710902872994

Hodges, K. (1998). *Child and Adolescent Functional Assessment Scale (CAFAS)*. Ann Arbor, MI: Functional assessment Systems.

Hyde, J., & Kammerer, N. (2009). Adolescents' perspectives on placement moves and congregate settings: Complex and cumulative instabilities in out-of-home care. *Children and Youth Services Review*, *31*(2), 265–273. http://dx.doi.org/10.1016/j.childyouth.2008.07.019

Illinois Department of Children and Family Services (IDCFS). (2010). *Policy Guide 2010.01 Child and Youth Investment Teams (CAYIT).* Chicago, IL: Illinois Department of Children and Family Services.
James, S. (2004). Why do foster care placements disrupt? An investigation of reasons for placement change in foster care. *Social Service Review*, *78*(4), 601–627.
James, S., Landsverk, J. S., Leslie, L. K., Slymen, D. J., & Zhang, J. J. (2008). Entry into restrictive care settings: Placements of last resort? *Families in Society: Journal of Contemporary Social Services*, *89*, 348–359.
Kroner, M. J., & Mares, A. S. (2009). Lighthouse independent living program: Characteristics of youth served and their outcomes at discharge. *Children and Youth Services Review*, *31*(5), 563–571. http://dx.doi.org/10.1016/j.childyouth.2008.10.011
Leeson, C. (2007). My life in care: experiences of non-participation in decision-making processes. *Child & Family Social Work*, *12*(3), 268–277.
Lindsey, D. (1992). Reliability of the foster-care placement decision—A review. *Research on Social Work Practice*, *2*(1), 65–80.
Los Angeles County Department of Children and Family Services. (2009). *Team Decision Making: The Resources Management Process (RMP/TDM)*. Los Angeles, CA: Los Angeles County Department of Children and Family Services. Retrieved from. http://lacdcfs.org/katieA/policies/010052540RMPv0109.pdf
Lyons, J. S. (2004). *Redressing the emperor. Improving our children's public mental health system*. Westport, CT: Praeger.
Lyons, J. S. (2009). *Communimetrics: A communication theory of measurement in human service settings.* New York, NY: Springer.
Lyons, J. S., & Abraham, M. E. (2001). Designing level of care criteria. In L. J. Kiser, P. M. Lefkovitz, & L. L. Kennedy (Eds.), *The Integrated Behavioral Health Continuum Theory and Practice* (pp. 91–106). Washington, DC: American Psychiatric Press.
Magura, S., Staines, G., Kosanke, N., Rosenblum, A., Foote, J., DeLuca, A., & Bali, P. (2003). Predictive validity of the ASAM Patient Placement Criteria for naturalistically matched vs. mismatched alcoholism patients. *American Journal on Addictions*, *12*, 386–397.
Martin, L. M., Peters, C. L., & Glisson, C. (1998). Factors affecting case management recommendations for children entering state custody. *Social Service Review*, *72*, 521–544.
Monnickendam, M., Savaya, R., & Waysman, M. (2005). Thinking processes in social workers' use of a clinical decision support system: A qualitative study. *Social Work Research*, *29*, 21–30.
Pfeiffer, S. I., & Naglieri, J. A. (1983). An investigation of multidisciplinary team decision-making. *Journal of Learning Disabilities*, *16*, 588–590.
Schwab, A. J., Bruce, M. E., & Mcroy, R. G. (1984). Matching children with placements. *Children and Youth Services Review*, *6*, 125–133.
Snyder, E. H., Lawrence, C. N., & Dodge, K. A. (2012). The impact of system of care support in adherence to wraparound principles in Child and Family Teams in child welfare in North Carolina. *Children and Youth Services Review*, *34*, 639–647. http://dx.doi.org/10.1016/j.childyouth.2011.12.010
Srebnik, D., Uehara, E., & Smukler, M. (1998). Field test of a tool for level-of-care decisions in community mental health systems. *Psychiatric Services*, *49*, 91–97.
Sunseri, P. A. (2005). Children referred to residential care: Reducing multiple placements, managing costs and improving treatment outcomes. *Residential Treatment for Children & Youth*, *22*(3), 55–66. http://dx.doi.org/10.1300/J007v22n03_04
The Praed Foundation (2010). Reliability and validity of the CANS. *About the CANS.* Retrieved from http://www.praedfoundation.org
U.S. Department of Health and Human Services (HHS) (2006). Preliminary FY 2005 estimates as of September 2006 (13). *The AFCARS Report.* Retrieved from http://www.acf.hhs.gov/
U.S. Department of Health and Human Services (HHS) (2010). Preliminary FY 2009 estimates as of July 2010 (17). *The AFCARS Report.* Retrieved from http://www.acf.hhs.gov/
U.S. Department of Health and Human Services (HHS) (2011). Preliminary FY 2010 estimates as of June 2011 (18). *The AFCARS Report*. Retrieved from http://www.acf.hhs.gov/
U.S. Department of Health and Human Services (HHS) (2012). Preliminary FY 2011 estimates as of July 2012 (19). *The AFCARS Report.* Retrieved from http://www.acf.hhs.gov/
Weigensberg, E. C., Barth, R. P., & Guo, S. (2009). Family group decision making: A propensity score analysis to evaluate child and family services at baseline and after 36-months. *Children and Youth Services Review*, *31*, 383–390. http://dx.doi.org/10.1016/j.childyouth.2008.09.001
Weiner, D. A., Schneider, A., & Lyons, J. S. (2009). Evidence-based treatments for trauma among culturally diverse foster care youth: Treatment retention and outcomes. *Children and Youth Services Review*, *31*, 1199–1205. http://dx.doi.org/10.1016/j.childyouth.2009.08.013
Winokur, M. A., Crawford, G. A., Longobardi, R. C., & Valentine, D. P. (2008). Matched comparison of children in kinship care and foster care on child welfare outcomes Families in society. *The Journal of Contemporary Social Services*, *89*, 338–346.
Wisconsin Department of Children and Families. (2011a). *Level of Need (LON) Algorithm 0-5*. Madison: Wisconsin Child Welfare Professional Development System. Retrieved from http://dcf.wisconsin.gov/memos/num_memos/DSP/2011/2011-03LON_Birth.pdf
Wisconsin Department of Children and Families. (2011b). *Level of Need (LON) Algorithm 5-17*. Madison, WI: Wisconsin Child Welfare Professional Development Team. Retrieved from. http://dcf.wisconsin.gov/memos/num_memos/DSP/2011/2011-03LON5_17.pdf