From the Director's Desk

August 24, 2020

Tools to Help Eliminate Biases—and Prevent Abuse

Good morning, and welcome to Monday. I hope this finds everyone well and staying healthy. As all of you know, there has been a great deal of needed focus on systemic racism and implicit bias recently. Of course, this is not a new topic in child welfare—overrepresentation of Black and brown children has been a source of continuing concern for quite some time. In a system that relies so heavily on the judgment of individuals as to whether or not a child is safe, how do we counterbalance the effect and eliminate the possibility of individual and/or systemic bias influencing decisions about safety, placement, and treatment of children?

There is a growing belief that the answer, at least in part, lies in big data and predictive modeling. Some of you may recall that almost exactly a year ago, I interviewed Emily Putnam-Hornstein, an associate professor at the University of Southern California School of Social Work and the director of [Children's Data Network](#), on National Children's Alliance's podcast, *One in Ten*. In the episode, "[Prediction as Prevention](#)," I ask Prof. Putnam-Hornstein to discuss her work in the field of predictive analytics and child welfare. We start the discussion with a statistic that is both startling and discouraging—she notes that just under 50% of African American and Black families in this country can expect to have a child welfare investigation. That is, of course, a vast overrepresentation in the system, as only 13.4% of the total population of the United States is African American or Black. And it is this statistic that compels much of Putnam-Hornstein's work, because if we are to understand how this came about, we must first understand who gets reported to the system, and from there, which cases are deemed to be of significant enough risk to warrant an investigation—and from there, a finding and/or services.

Tackling the first issue—who gets reported—we know that of the 3.5 million (rounded) children who were reported to child protective services in 2018, only 678,000 (rounded) of those cases resulted in a confirmed case of abuse, and even fewer were at risk of an out-of-home placement.[1] The vast majority of reports were unsubstantiated. This raises a number of points: the need for better training in identifying signs of abuse so reports are more accurate and far fewer unwarranted reports come into the system in the first place; the need to look at the way bias influences who gets reported for abuse; and, once reported, the need to reduce and eliminate bias in what cases are assigned for investigation.

Putnam-Hornstein's research asked a critical question: For all the time we spend on cases that turn out to be low- risk or no-risk, are we missing the more serious cases? She and her colleagues wanted to find a way to streamline risk

assessment, improve reliability, reduce bias, and ensure that it would not place additional burdens on an already overworked and understaffed system.

To accomplish this, they looked at the use of harvesting information we already have—big data collected both in the child welfare system and in other systems such as health care. Using the data, the researchers created algorithms to assess risk on the front end, to be used as part of the determination of whether to investigate. And that's the key here—Putnam-Hornstein emphasizes that predictive analytics is <u>never</u> a substitute for experienced judgment. Rather, it is a tool to be used in conjunction with clinical judgment, but not in the place of a caseworker and supervisor's judgment altogether.

But isn't it also true that implicit bias can be built into algorithms? Putnam-Hornstein agrees that it can, but she also discusses with me the fact that much of the bias in the system we see now is the result of the human tendency to conflate race and risk. If done correctly, predictive analytics eliminates that tendency, and can look at the entirety of a family's history and compare that with data on the likelihood of future events—without race as a factor. In Putnam-Hornstein's work with child protective services in Allegheny County, Pennsylvania, the predictive analytics tool was evaluated by an independent third party.[2] The key findings indicate that the tool accurately predicted high risk in cases and that its use resulted in a slight but nonetheless significant reduction in racial disparities in case openings, such that the number of screened-in cases decreased slightly for African American/Black children and increased slightly for white children.

Putnam-Hornstein's work with predictive analytics and predictive risk modeling holds promise for intervention work—but even more so for prevention work. As she herself notes, there are conversations going on around the country about how risk models and big data "can be used to help move the conversation upstream ... [so that] children born into families where the parents may need more support are

prioritized for home-visiting and other early interventions."[3]

The benefit of using big data and predictive analytics "upstream" in prevention work is that we can move it away from individual cases and further reduce the risk of data being used in a disproportionate or punitive way. If we're using it for prevention work, then by necessity, we are talking about using it to identify families who are in need of greater support and services to help them avoid entering the child welfare system in the first place.

In fact, researchers are already hard at work on this very approach. Dr. Dyann Daley, pediatric anesthesiologist and now CEO of Predict-Align-Prevent, conducted research using a method known as risk terrain modeling (RTM) that provides an analysis of the cumulative effect of environmental factors thought to be conducive to child abuse. Using this information, Daley and her team of researchers were able to create a highly accurate prediction model for future substantiated child maltreatment cases in the city of Fort Worth, Texas. Their results are published in a study titled "Risk terrain modeling predicts child maltreatment." Rather than looking at individual cases, the researchers analyzed "risk clusters," defined as "locations of acute accumulations of problematic factors" such as crime statistics (focusing on aggravated assaults, robberies, murders, domestic violence, and narcotics crimes, the presence of gangs and street prostitution), the presence of bars and nightclubs licensed to serve alcoholic beverages past midnight, and data on all forms of child abuse including neglect; physical, emotional, and sexual abuse; and abandonment, as well as trafficking of children ages 0 to 17.

Using this data, researchers were able to accurately predict "52% of all instances [of substantiated child maltreatment] during the subsequent year in only one-tenth of the city's area that was identified as having the most problematic aggregation of risk factors. Moreover, a total of 98% of all substantiated future cases occurred in

discrete areas that were correctly flagged as having elevated risk." Id., p. 34.

But what's most important for our purposes is less the accuracy than the intent. Because the point of using risk terrain modeling was not punitive, but rather preventative, identifying those areas accurately means that the tool can be used to "enable future interventions to optimize the allocation of scarce prevention and treatment resources in narrowly confined, highest need locations." It changes "the paradigm of how children can be located in discrete geographic areas before they are harmed by abuse and neglect." Id., p. 35. And it "allows child welfare professionals, community organizations, faith-based groups, and social services providers to concentrate resources and support where children and families need them the most." Id. Finally, using this system could help with "improvements to the recruitment and training of competent, trauma-informed foster and adoptive families within the neighborhood [which] could provide an easier transition for children already within the child welfare system and could represent an effort aimed at changing social norms around effective parenting." Id.

Technology and big data are our future—and the possibilities for positive growth and change within child welfare and in terms of outcomes for children are limitless. I strongly encourage you to listen (or re-listen) to the "Prediction as Prevention" podcast episode, and to take some time to read through the studies published by Prof. Putnam-Hornstein and Dr. Daley. Learn how big data and predictive analytics can shape the future of child abuse prevention work, and discuss with your colleagues what's being done in your community, state, and region to implement this work. Even small changes that help children to have better outcomes make a significant difference in the trajectory of their lives.

As always, I appreciate all that you are doing to keep children and families safe during this time, and I wish you all well.

Warmest regards,
Teresa

[1]U.S. Department of Health & Human Services, Administration for Children and Families, "Child abuse, neglect data released," January 15, 2020.

[2]For more information on Prof. Putnam-Hornstein's work with predictive analytics, see "Preventing severe and fatal child maltreatment: Making the case for the expanded use and integration of data," *Child Welfare*, November 2013. For the most recent publication on her work with Allegheny County, Penn., see "Hospital Injury Encounters of Children Identified by a Predictive Risk Model for Screening Child Maltreatment Referrals: Evidence from Allegheny Family Screening Tool," *JAMA Pediatrics*. Published online August 3, 2020.

[3]"Prediction as Prevention" (31:20)

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