



# Big Data = Big Problems + Little Promise: A formula for false hope in protecting children

by Charissa Huntzinger  
*Policy Analyst*

## Key Points

- Like Netflix uses data to forecast your movie interests, child welfare agencies are using data to identify children at risk of future abuse to intervene in advance.
- Predictive risk models implemented in other states have created more problems than they have solved, leading several states to abandon those efforts.
- Using data analytics to predict child maltreatment does not eliminate bias but legitimizes it by cloaking it in the mantle of empirical science.
- There is a clear distinction between families in need and families at risk. Predictive analytics blurs this line.
- In light of the spectacular failures and extreme risks, child welfare agencies should be hesitant to latch onto the false hope of predictive analytics.

## Predictive Analytics in Child Welfare

State foster care systems are charged with the unenviable and largely impossible task of protecting children from maltreatment. Perhaps no area of state policy is more emotionally laden, politically explosive, and perplexingly complex. State agencies must decide whether to pull a child out of a home—with all the attendant trauma and uncertainty—or to leave that child at home and possibly in danger ([A.E. Casey](#)).

Striking this balance has proven difficult. Across the nation, foster care systems are plagued by low family reunification rates, long lengths of stay for children in foster care, incongruencies between the child welfare services offered and actual parental needs, and unsustainable increases in the number of children under state care ([DHHS 2017b](#)).

Rather than accept the attendant inevitabilities of fragile families and troubled individuals and admitting the relative powerlessness of government to prevent child maltreatment, policymakers perennially search for a broad-spectrum, quick-fix solution.

Although there is no easy answer to the many problems plaguing the foster care system, the emergence of predictive analytics in child welfare agencies is gaining attention as a quick fix ([Church and Fairchild, 68](#)). Predictive analytics promises to use the same technology that suggests products on Amazon and movies on Netflix to foretell child maltreatment and to intervene before it occurs. Despite growing interest in the use of predictive analytics, significant ethical challenges must be addressed before applying these models to child welfare.

This brief discusses the current state of predictive analytics in child welfare, from the types of predictive models available to its current applications. It outlines concerns about the tool's equity and efficacy, and then critically evaluates the question: Should predictive analytics be used in child welfare?

## What Is Predictive Analytics?

The dawn of the age of big data has provided two ways of processing data into actionable information: descriptive and predictive analytics. Descriptive analytics summarizes past events. Predictive analytics anticipates the future.

In child welfare, predictive analytics refers to the application of statistical algorithms to data in order to estimate the likelihood of future maltreatment. These models rely on current and historical data. Predictive risk modeling (PRM) is a specific type of predictive analytics that uses data patterns to identify risk factors and to stratify individuals based on the likelihood of a future event—specifically, child abuse or neglect ([Packard, 2](#)). Predictive modeling has been implemented in fields such as finance, health care, and criminal justice, but has only recently been introduced to child welfare.

The efforts of child protection agencies to implement predictive analytics have focused on predicting risk of abuse or neglect, maltreatment recurrence, and child fatalities ([Cuccaro-Alamin et al., 294](#)). Agencies have utilized predictive models at different stages of service: at the intake of a maltreatment allegation, to aid caseworkers during investigations, or to identify at-risk locations and focus child welfare services ([Teixeira and Boyas, 7](#)).

## Summary of Current Applications of Predictive Analytics

### *Allegheny County, Pennsylvania*

The Allegheny Family Screening Tool (AFST), implemented by the Department of Children and Youth Services in Pennsylvania, is a widely cited example of predictive analytics in child welfare, but it has been fraught with logistical problems and privacy concerns. Beginning in 1994, Allegheny County, Pennsylvania, began sweeping organizational changes including the restructuring of data storage into a central data warehouse ([Packard, 14](#)). In 2016, Allegheny County began using AFST to target families for intervention based on data analytics.

When a call comes into the child abuse hotline alleging abuse or neglect, AFST produces a risk score for the child ([Packard, 14](#)). The score forecasts the statistical probability a child will be taken into care of the state within the next year. The scores are based on risk factors from governmental and nongovernmental data sources.

### Data pulled from need-based programs are more indicative of family need than child safety.

Although the algorithm has access to an impressive array of centralized data, the algorithm's maltreatment criteria have a clear bias toward identifying poor communities. The AFST pulls data from programs like the Temporary Assistance for Needy Families (TANF) program and county medical assistance to make predictions—data that is more indicative of family need than child safety. The disparity is also shown in the variables omitted by the tool. Families using private services for drug counseling or financial assistance are not tracked ([Eubanks](#)).

Even though the algorithm poses ethical concerns related to bias, supporters of predictive analytics argue that those concerns are substantially outweighed by its potential benefits ([Dare](#)). This argument presupposes the algorithm's effectiveness. Yet years after implementation, there is no official evaluation of the tool's outcomes or success. Without

empirical support, claims that the AFST helps children in a meaningful way are specious at best.

### *Hillsborough County, Florida*

Another prominent example of predictive analytics is the Rapid Safety Feedback (RSF) tool, a predictive model introduced in Hillsborough County, Florida, after a series of high-profile child fatalities.

The tool was developed by a private child welfare service provider, Eckerd Kids. RSF uses historical data, including substance abuse history or parent involvement in foster care, to predict which cases are at the highest risk of serious injury or fatality. A quality assurance process then determines if services to a family with an open case are being impactful ([Packard, 15](#)). During development, Eckerd partnered with MindShare Technology, a Florida-based data mining and analytics company, to construct a system that can access real-time data and improve caseworkers' handling of maltreatment cases ([CECANF, 39-40](#)). This data is interpreted by agency workers as predictions of recidivism, re-abuse, and aging out ([Packard, 15](#)).

Florida's RSF is one of several examples that proponents of predictive analytics use to support moving forward with expanding big data in child welfare. The supposed success of this tool, however, is undermined by a lack of any official evaluation of the tool's outcomes. Current studies cite the absence of abuse-related fatalities in the county since implementation as definitive proof of the tool's success ([CECANF, 41](#)).

Bryan Lindert, senior quality director at Eckerd Kids, testified before Congress that “in Hillsborough, there were no maltreatment fatalities in the three year period following implementation of the program” ([Lindert, 3](#)). However, Richard Wexler ([2016](#)), executive director of the National Coalition for Child Protection reform, points out that the county hired a wave of new caseworkers to address the failures of the system at the same time it debuted RSF. This and other factors at play in the agency (e.g., changing the types of fatalities labeled as maltreatment) occurring concurrently with the implementation of RSF cause Wexler to doubt the effectiveness of RSF. The presumption that RSF ended the series of child fatalities confuses correlation with causation—that the tool alone caused the decrease in child fatalities. The Commission to Eliminate Child Abuse and Neglect Fatalities noted that “to prevent fatalities, workloads must support the level of contact with families necessary to assess the current status of a child's safety and a caregiver's progress” ([CECANF, 77](#)).

Despite a lack of empirical support, Eckerd is rolling out variations of the RSF tool in Illinois, Ohio, Indiana, Maine, Louisiana, Tennessee, Connecticut, and Oklahoma. While Florida reports success with the model, other states have experienced contradictory results. The Illinois Department of Children and Family Services (DCFS) Director Beverly Walker commented that the department would not be moving forward with RSF implementation because it “didn’t seem to be predicting much” ([Jackson](#)). Out of 7,048 family case openings in the state, more than 4,100 children were assigned a score of 90 out of 100, indicating the probability of death or serious injury. Walker explained that RSF was leading to systemwide overreaction that buried cases of actual risk under a mountain of false positives ([Jackson](#)).

In light of the disastrous performance of the tool in Illinois and without an official evaluation of Florida’s RSF, the expansion of Eckerd’s RSF into more states is unwarranted.

### *Los Angeles County, California*

The Los Angeles County Department of Children and Family Services contracted with a private company, SAS, in 2014 to experiment with predictive analytics in their child welfare system. The Approach to Understanding Risk Assessment (AURA) model tracked child fatalities and histories of reported abuse in these families between 2011 and 2012. SAS then took data from these cases, such as previous abuse referrals and substance abuse, to produce a risk score. Scores were applied to cases from 2013 to determine if the tool had predictive power ([Packard, 16](#)).

AURA correctly identified 171 cases at the highest risk for abuse. However, it also incorrectly classified 3,829 children as “high risk” who were not at risk for a negative outcome ([Nash, 10](#)). In other words, the 171 true positives came at the expense of 3,829 false positives.

The AURA experiment ended in 2014 with a final decision by DCFS to no longer pursue the program. A report to the Los Angeles County Board of Supervisors detailing the project’s findings cited two primary issues with the model ([Nash, 10](#)). The false positive rates produced by the assessment had potential to overwhelm the system, and the assessment was a “black box” that lacked transparency about why certain scores were produced ([Nash, 9](#)). SAS claims details of the algorithm, including the specific methodology of arriving at risk scores, are proprietary—meaning government data are run through an opaque black box, yielding a score that prompts government action but without an understanding of why action is being taken.

The Los Angeles County DCFS is currently partnering with Children’s Data Network to develop a PRM that seeks

to remedy the transparency issues associated with AURA ([Nash, 10](#)).

### *Fort Worth, Texas*

A geospatial analysis technique called the Risk Terrain Model (RTM) was piloted in Fort Worth, Texas, in 2013 and 2014 ([Daley et al., 32](#)). RTM analyzes the interaction of environmental factors with past child maltreatment to predict future maltreatment cases ([32](#)). The goal of the tool is to find geographic concentrations of children with the highest risk of abuse or neglect and concentrate resources in those geographic areas ([34](#)). The tool examines the geographic distributions of risk criteria and produces a map that gives a risk score between 1 and 150 for every half-block within the city boundaries ([32](#)). The areas are then categorized by projected risk level.

A tool that identifies more than half of all residential neighborhoods as risky may be of limited utility—especially when it does little more than over-identify poor, residential neighborhoods.

Researchers used 10 factors in designing the risk assessment, ranging from poverty to drug crimes to proximity of bars and liquor stores ([Daley et al., 32](#)). Utilizing those factors, the model designated more than 40 percent of the city as areas of elevated risk for abuse and neglect ([33](#)). Ninety-eight percent of substantiated maltreatment cases took place in that 40 percent of the city ([33](#)). Of course, the remaining 60 percent includes large swaths of the city where few children live (i.e., downtown business district, industrial areas).

A tool that identifies more than half of all residential neighborhoods as risky may be of limited utility—especially when it does little more than over-identify poor neighborhoods. The model confuses poverty with maltreatment by using measures of poverty as the factor most predictive of abuse and neglect. This is not only dangerous for poor families but raises questions about the model’s utility.

RTM also relies upon voluntary family engagement in child protection services focused on an area. However, because it does not differentiate types of maltreatment or identify the causes or conditions related to maltreatment, RTM does not inform the services needed in the poor, high-risk neighborhoods it targets. As such, it may actually increase resource

mismanagement by identifying where services are arguably needed but not what services would decrease risk—resulting in kitchen-sink service allocation in those areas.

### Concerns Surrounding Predictive Analytics

Ideally, predictive analytics should increase precision, decrease subjectivity, and provide consistency in operator-driven risk assessments. Even after resolving barriers to implementation like data acquisition, data quality, and costs, concerns persist surrounding the equity, reliability, validity, and utility of predictive analytics. The uncertainty of these models and lack of adequate assessments are enough to call into question whether predictive analytics, in its current state, is an effective use of already limited resources.

#### Privacy and Consent

Privacy concerns are one of the most overlooked issues with predictive analytics, as many proponents of predictive models abandon individuals' natural privacy rights in the name of child protection ([Dare, 53](#)).

Predictive analytics relies on data sharing and the use of individuals' personal information to produce a risk assessment. There has been relatively little discussion on methodology for or necessity of protecting child or family privacy and information. Too often, privacy rights are restricted in the name of the public good or the best interest standard. Children must be protected, but a disregard for privacy rights presents its own risks ([Gerstein](#)).

In certain cases, preventative services could provide aid for families identified by predictive models as having high-risk levels. However, child protection agencies should not have the authority to intervene in a family until a report has been received by the system ([Logan 2018](#)). Running models on families who have not given consent or voluntarily engaged in preventative programming with child protection services raises concerns of abuse and government overreach ([Teixeira and Boyas, 10](#)). At best, predictive analytics tools have little efficacy if families opt not to use the offered preventative services. At worst, it infringes upon the privacy of the child and the family.

Privacy concerns are further exacerbated by the strain placed on families with high-risk scores who have no substantiated maltreatment allegations ([Dare and Gambrill, 3](#)). Predictive models produce an estimate of risk in a household, *not a finding of abuse or neglect*. Thus in many cases, families who have not or will not maltreat their child, are identified by the tool (i.e., false positive). Families are then subject to stigmatization and targeted as potential abusers for actions that may never have come to pass ([Dare and](#)

[Gambrill, 4](#)). There is a clear distinction between families in need and families at risk. Predictive analytics blurs this line.

When child welfare agencies, private service providers, or others use data without consent to identify at-risk families, these entities infringe on family and parental privacy. Predictive models generate risk assessments by drawing information from databases without consent from the suppliers of the data or from the families themselves ([Packard, 27](#)). Most data is collected in a manner that obscures the relationship between data provider and data user ([Dare and Gambrill, 2](#)). The individuals who are being assessed do not give consent in any meaningful way to provide data for the purpose of a risk assessment, particularly public records like birth data and hospital sector data ([Vaithianathan et al., 12](#)). It should be noted that when predictive models are used solely at the point of intake, these concerns are somewhat mitigated by the fact that the allegation itself serves as grounds for further inquiry into the data.

Using predictive tools to estimate a family's risk, based on data accessed without consent, strips families who have not been or may not be found guilty of maltreatment of their natural privacy rights.

#### Equity

Current practice in child protective agencies relies on human judgment to determine if an allegation must be investigated, leaving room for human bias. Yet the same bias exists within predictive analytics but is perilously presented as objective and scientifically sound.

### Human bias exists within predictive analytics but is perilously presented as objective and scientifically sound.

One of the goals of predictive analytics is to uniformly apply a set of risk indicators to each case, effectively removing clinical bias or discrimination ([Cuccaro-Alamin et al., 295](#)). The selection of these predictors, however, is not arbitrary. In Allegheny County's AFST tool, many of the measures used are direct correlates to poverty, including public behavioral health services, county medical assistance, and public welfare receipts ([Eubanks](#)). In fact, the tool explicitly adopts the socioeconomic status of each ZIP code area as a proxy of risk. Using correlates of poverty as indicators of risk disproportionately targets poor communities and communities of color ([Capatosto, 4](#)). The underlying risk of

selecting proxies for child abuse is that the bias sought to be avoided gets embedded into the tool.

## Using correlates of poverty as indicators of risk disproportionately targets poor communities and communities of color.

Previous involvement with child protective services is a main risk criterion in predictive models for anticipating maltreatment ([Sledjeski et al., 29](#)). This metric unduly affects minority families, as they are overrepresented in the system. African-American children are represented in the foster care system at 1.8 times their rate in the general population ([Child Welfare Information Gateway, 2](#)). Fifty-three percent of African-American children will be subjected to a child protective services investigation by age 18 ([Kim et al.](#)). These algorithms include criteria overwhelmingly characteristic of specific socioeconomic and racial backgrounds, which necessarily causes these groups to be risk-targeted ([Capatosto, 4](#)). Families vulnerable to high-risk scores are more likely to be investigated and subjected to state interference, which can be very harmful to children and families ([Logan 2017](#)). More exposure to investigations increases the likelihood of child removal, which has the potential to further exacerbate the racial disparity in foster care.

As Kirwan Institute researcher Kelly Capatosto states, “Individual-level predictions ... are more likely to target people for who they are (race, proximity to crime, class, education level, etc....) rather than on the basis of observable behavior” ([6](#)).

### Transparency

To compound the problem of inequitable data, very little transparency surrounds the exact metrics comprising predictive algorithms ([Church and Fairchild, 73](#)). Often this lack of transparency arises from the developer’s proprietary interest in protecting their algorithm from competitors. The economic interest of private contractors supersedes the ethical interest of state child welfare agencies toward their citizens.

Issues with data transparency increase with machine learning, where algorithms “adjust to new relationships in the data” and improve without being specifically programmed to do so ([Cuccaro-Alamin et al., 293](#)). The evolving and autonomous nature of the digital algorithm makes it difficult for the developers themselves to know exactly why a specific decision is made ([Church and Fairchild, 73](#)).

When the potential exists for liberty to be infringed upon, in this case for families subject to CPS involvement, transparency in the name of ethical standards should be a priority. Government applications of data must be subject to oversight and accountability. Locking the criteria and methodology used to target citizens in a proprietary “black box” permits actions of government that infringe on family sovereignty to escape review.

### Validity

A goal for predictive analytics is to increase predictive accuracy in child protection, but existing models have either conspicuously failed to do this or provided no evidence of success. In light of these deficiencies, a state of uncertainty surrounds the use of predictive analytics in child welfare ([Russell, 183](#)).

Predictive analytics is designed to predict the rare event of child fatalities, yet research suggests the performance of predictive tools decreases as events become increasingly rare ([Cuccaro-Alamin, 295](#)). There were an estimated 1,750 child fatalities related to maltreatment in the U.S. in 2016 but 7.4 million allegations of child abuse ([DHHS 2017a, ix-x](#)). Child abuse fatalities are undeniably tragic, but thankfully rare ([Cuccaro-Alamin, 295](#)). Preventing fatalities is, and should be, a primary goal of child welfare services and policy, but an algorithm that is anything short of precise in its application can be more costly for at-risk children than current tools that use professional judgment.

Predictive analytics yield four different outputs. A true positive or true negative indicates the model predicted an outcome correctly. When the model predicts incorrectly, these outcomes are called false positives and false negatives. The higher the number of true positives, the more accurate the tool.

When Los Angeles Department of Children and Family Services implemented AURA, reports stated the tool correctly identified 171 cases of severe maltreatment, a 76 percent rate of success ([Church, 71](#)). The predictive model increased the yield of true positives. This number alone, however, can be misleading in its interpretation. Citing only this statistic ignores the number of cases where the event was predicted to happen but did not happen. In the DCFS study, the algorithm incorrectly identified 3,829 cases as high risk, a false positive rate of 96 percent ([Church, 71](#)). If it had intervened, the department would have responded to thousands of cases in which there was no risk of severe maltreatment or death.

For the 171 cases where intervention perhaps could have protected a child, the use of the algorithm would have

actually diverted limited resources and staff away from these critical cases ([Church, 72](#)) to respond to the 3,829 cases falsely identified as high risk. Before employing predictive analytics in child welfare, the algorithm must not only prove it can predict maltreatment, but it can do so without collateral damage.

To be sure, current decision-making procedures, namely intake worker judgment, can result in the mislabeling of cases as high or low risk ([Gambrill and Shlonsky, 818](#)). The question, then, is whether false positives or negatives should come in the form of human error in specific cases, subject to review and reassessment, or from algorithmic miscalculation within a “black box” that implicates entire classes of families and children for increased scrutiny based on who they are, rather than what they have done.

### *Utility*

The usefulness of the tool is related to its practical guidance for child protection workers, to identify which cases demand intervention and which do not and, ideally, what level of intervention is required.

A benefit of predictive analytics is that algorithms are more consistent in assessing risk than intake workers ([Cucarro-Alamin et al., 293](#)). The logic follows that predictive analytics can standardize the assessment practice because the metrics being used are objective. Although models use different scales, their results are the same, a single number representing a vast amount of complex, dynamic information.

Standardized, numerical risk scores vastly oversimplify the nuance and complexities found in the data and lead to overreliance on the mathematical formula, rather than the measured application of professional judgment to known facts ([Church and Fairfield, 77](#)). Without supplying context for a particular risk score, the algorithm neither supplements the workers’ decision-making nor teaches the worker how to identify those particular risk factors in future cases ([Church and Fairfield, 78](#)). In fact, agencies have expressed concern that dependence on risk assessments could incentivize risk-averse behavior, causing more marginal cases to be

referred for investigation, increasing caseloads ([Teixeira and Boyas, ii](#)).

The overreliance on a single number directly relates to the algorithm’s utility ([Church and Fairfield, 77](#)). In an ethical review of Allegheny County’s AFST, the researchers ([Dare and Gambrill](#)) raise concerns over the gap between a risk score and an effective response: Why increase prediction capabilities if the child-protective services offered to families are not evidence-informed? Why focus on better prediction if the staff are not trained to conduct informed assessments? The tendency to view predictive tools as a panacea for all that ails child protective systems leads to atrophy in other crucial areas of child welfare practice.

Predictive analytics is only useful if, in the end, it protects the children and families it is serving. The introduction of algorithms has instead shown signs of supplanting clinical judgment and having very little practical effect on services to families ([Dare, 61](#); [Teixeria and Boyas, 9](#)).

### **Conclusion**

Without more definitive answers to questions about equitable application of predictive analytics across subpopulations and a more rigorous effort to improve transparency, accuracy, and usefulness, the costs of predictive analytics are too high. Those costs include exacerbating the confusion between poverty and maltreatment; targeting families based on sociodemographic factors rather than risk; and weaponizing government data against families without consent or accountability.

In an area where resources are already limited, a high level of scrutiny must be applied to a program that promises to fix problems without ample evidence that it is capable of doing so. Predictive analytics represents hope in the often-hopeless world of protecting children from abuse and neglect. Unfortunately, it is a false hope. In its current state, predictive analytics is not a quick fix, or even a viable solution. Rhema Vaithianathan, a pioneer in the predictive analytics field, warns “that policy makers and practitioners, because they are under so much pressure to do something, just end up adopting things. We need to go slowly” ([Packard, 6](#)). ★

## References

- A.E. Casey (Annie E. Casey Foundation). 2009. [\*Fixing a Broken System\*](#). Annie E. Casey Foundation.
- Capatosto, Kelly. 2017. [\*Foretelling the Future: A Critical Perspective on the Use of Predictive Analytics in Child Welfare\*](#). The Kirwan Institute.
- CECANF (Commission to Eliminate Child Abuse and Neglect Fatalities). 2016. [\*Within Our Reach: A Strategy to Eliminate Child Abuse and Neglect Fatalities\*](#). Commission to Eliminate Child Abuse and Neglect Fatalities.
- Child Welfare Information Gateway. 2016. [\*Racial disproportionality and disparity in child welfare\*](#). Children's Bureau, U.S. Department of Health & Human Services.
- Church, Christopher, and Amanda Fairchild. 2017. "In Search of a Silver Bullet: Child Welfare's Embrace of Predictive Analytics." *Juvenile & Family Court Journal* 68(1): 67-81.
- Cuccaro-Alamin, Stephanie, Regan Foust, Rhema Vaithianathan, and Emily Putnam-Hornstein. 2017. "Risk Assessment and Decision Making in Child Protective Services: Predictive Risk Modeling in Context." *Children and Youth Services Review* 79: 291-298.
- Daley, Dyann, Michael Bachmann, Brittany Bachmann, Christian Pedigo, Minh-Thuy Bui, and Jamye Coffman. 2016. "Risk Terrain Modeling Predicts Child Maltreatment." *Child Abuse & Neglect* 62: 29-38.
- Dare, Tim and Eileen Gambrill. 2017. [\*Ethical Analysis: Predictive Risk Models at Call Screening for Allegheny County\*](#). Allegheny County Department of Human Services.
- Dare, Tim. 2013. [\*Predictive Risk Modelling and Child Maltreatment an Ethical Review\*](#). University of Auckland.
- DHHS (U.S. Department of Health & Human Services). 2017a. [\*AFCARS Report No. 24 - Preliminary FY 2016 Estimates as of Oct 20, 2017\*](#). Children's Bureau, U.S. Department of Health & Human Services.
- DHHS (U.S. Department of Health & Human Services). 2017b. [\*Child Maltreatment 2016\*](#). Children's Bureau, U.S. Department of Health & Human Services.
- Eubanks, Virginia. 2018. "A Child Abuse Prediction Model Fails Poor Families." *Wired*, Jan. 15.
- Gambrill, Eileen, and Aron Shlonsky. 2000. "Risk Assessment in Context." *Children and Youth Services Review* 22(11-12): 813-837.
- Gerstein, Robert. 1978. "Intimacy and Privacy." *Ethics*, 89(1): 76-81.
- Jackson, David, and Gary Marx. 2017. "Data mining program designed to predict child abuse proves unreliable, DCFS says." *Chicago Tribune*, Dec. 6.
- Kim, Hyunil, Christopher Wildeman, Melissa Jonson-Reid, and Brett Drake. 2017. "Lifetime Prevalence of Investigating Child Maltreatment among US Children." *American Journal of Public Health*, 107(2): 274-280.
- Lindert, Bryan. 2016. [\*The Heroin Epidemic and Parental Substance Abuse: Using Evidence and Data to Protect Kids from Harm\*](#). Testimony before the U.S. House of Representatives Committee on Ways and Means, Subcommittee on Human Resources, May 18.
- Logan, Brandon. 2017. [\*Effects of CPS Involvement on Child Wellbeing\*](#). Texas Public Policy Foundation.
- Logan, Brandon. 2018. [\*Family Privacy and Parental Rights as the Best Interest of Children\*](#). Texas Public Policy Foundation.
- Nash, Michael. 2017. [\*Examination of Using Structured Decision Making and Predictive Analytics in Assessing Safety and Risk in Child Welfare\*](#). County of Los Angeles, Office of Child Protection.

- Packard, Thomas. 2016. [\*SACHS Literature Review: Predictive Analytics in Human Services\*](#). The Academy for Professional Excellence, San Diego State University School of Social Work.
- Russell, Jesse. 2015. "[Predictive analytics and child protection: Constraints and opportunities](#)." *Child Abuse & Neglect* 46: 182-189.
- Schwartz, Ira, Peter York, Eva Nowakowski-Sims, and Ana Ramos-Hernandez. 2017. "[Predictive and prescriptive analytics, machine learning and child welfare risk assessment: The Broward County experience](#)." *Children and Youth Services Review* 81: 309-320.
- Sledjeski, Eve M., Lisa C.Dierker, Brigham, Rebecca Brigham, and Eileen Breslin. 2008. "[The use of risk assessment to predict recurrent maltreatment: A classification and regression tree analysis \(CART\)](#)." *Prevention Science* 9(1):28-37.
- Teixeira, Christopher, and Matthew Boyas. 2017. [\*Predictive Analytics in Child Welfare: An Assessment of Current Efforts, Challenges and Opportunities\*](#). Department of Health and Human Services.
- Vaithianathan, Rhema, Emily Putnam-Hornstein, Nan Jiang, Parma Nand, and Tim Maloney. 2017. [\*Developing Predictive Models to Support Child Maltreatment Hotline Screening Decisions: Allegheny County Methodology and Implementation\*](#). Centre for Social Data Analytics.
- Wexler, Richard. 2016. [\*Big Data is Watching You\*](#). The National Coalition for Child Protection Reform.

## About the Author



**Charissa Huntzinger** is a policy analyst in the Center for Families & Children at the Texas Public Policy Foundation. She graduated from Baylor University with a B.A. in both political science and French.

## About Texas Public Policy Foundation

The Texas Public Policy Foundation is a 501(c)3 non-profit, non-partisan research institute. The Foundation's mission is to promote and defend liberty, personal responsibility, and free enterprise in Texas and the nation by educating and affecting policymakers and the Texas public policy debate with academically sound research and outreach.

Funded by thousands of individuals, foundations, and corporations, the Foundation does not accept government funds or contributions to influence the outcomes of its research.

The public is demanding a different direction for their government, and the Texas Public Policy Foundation is providing the ideas that enable policymakers to chart that new course.

