In 2009, a statistician, lawyer, and child welfare director teamed up to address Georgia’s finding of nonconformity following a federal review that identified the need to improve permanency outcomes for children in long-term foster care (Meredith, 2010). Using child welfare administrative data, the statistician developed a gradient boosted regression tree algorithm to fit a multivariate model that could accurately identify the children least likely to achieve legal permanency. The lawyer assembled a team to review the identified cases and to come up with a plan to help those children achieve legal permanency. The child welfare director lent her authority to implement the project statewide and gave the project its name: the Cold Case Project (“CCP”).

Six years later, CCP was implemented in South Carolina, the fourth such state to follow Georgia’s lead and use predictive analytics to promote permanency under this project (Horn, 2016). In South Carolina, CCP staff reviewed over 90 cases, each of which was compelling in its own right and screamed for accountability. These children were in legal and emotional limbo and needed a fearless champion. Anthony was one such child. His case, and CCP more generally, demonstrate how much growth is needed to implement predictive analytics well. This article extends the authors’ ongoing scrutiny of the appropriate ethical, moral, and legal framework for developing predictive models and for using their outputs in child welfare.

Anthony spent most of his life in foster care. By the time he reached age 16, he had experienced 17 placement changes while in foster care. He loved country music, wanted desperately to go hunting with his friends, and hoped to be adopted by a family that would simply love him. According to the predictive model, that last prospect seemed unlikely.

But then CCP re-energized efforts on his behalf. CCP staff reviewed his case and sounded the alarm based on all that had gone wrong at the hands of the system. CCP staff came up with an aggressive plan to find Anthony a family. Of course they were, by and large, shooting from the hip, because knowledge about what works in child welfare is limited. Perhaps

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3 In this article, predictive analytics refers to the process of applying statistical algorithms to data to make informed guesses about future events.
4 A pseudonym. Anthony’s story is real. To protect Anthony’s privacy, citations for all information referenced in this article are on file with the authors.
5 We use the term system in this article to refer broadly to all the various people, organizations, and infrastructure involved in serving children and families that are the subject of child abuse and neglect allegations.
more fatal, CCP’s plans for Anthony were, like most plans CCP staff recommend, unconventional. And while innovation and risk-taking in government is often necessary to find families for children like Anthony, it is not often tolerated.6

For Anthony, CCP respected his wishes and advocated for him to remain connected to his kin, despite the system’s concern related to the safety of that plan. For Anthony, this meant fighting for him to be allowed to go hunting with his friends, like most kids in South Carolina would be allowed to do, but not a kid whose parent is the State. In the midst of their advocacy, CCP staff learned Anthony had run away from his group home and was on AWOL status. For weeks, CCP staff called for updates. Time after time, the agency responded that nobody knew his whereabouts. This was not the first time that Anthony had run away from foster care.

CCP was an early application of predictive analytics in child welfare. Staff who created and worked on the project are proud of the undertaking and stand by its implementation (Rawlings, 2018). The creators of CCP knew the right question to ask: which children in foster care were least likely to achieve permanency before they turned 18? It was the right question because there was agreement that emancipation was an unacceptable outcome for children involuntarily separated from their families. It was also the right question because Georgia needed to document how the state’s poor performance for children in long-term foster care was being addressed, as mandated by a recent federal review.

CCP was premised on an algorithm that could predict, quite accurately, the children most likely to age out of foster care. This was a critical design choice: data, not intuition, were used to identify the most at-risk children like Anthony. The ensuing interventions had a critical design flaw, however. As with Anthony, project staff reviewed cases, generated outrage, but largely relied on intuition and experience to proffer interventions they simply hoped would address the underlying causes. It feels sacrilegious to be critical of CCP, as we believe it is one of the most important innovations conducted in child welfare that partners legal and agency stakeholders. Still, sometimes the most difficult and least desirable lessons are the ones we learn the most from. Many years of CCP implementation inform this article well, even if that requires a minor mea culpa.

Child welfare professionals need to be proficient and skeptical consumers of predictive analytics. It is not enough to draw a line in the sand and classify predictive analytics as either the greatest or worst innovation in child welfare. Rather, it is imperative to continue to embrace the complexity of predictive analytics by asking critical questions about its design and use. In an earlier article, we identified a number of prerequisites that should be carefully explored prior to implementing predictive analytics in high-stakes fields like child welfare (Church & Fairchild, 2017). First, we called for child welfare professionals to develop basic competencies in predictive analytics terminology. That is, if child welfare seeks to incorporate predictive analytics into their day-to-day operations, the field should understand and be able to contextualize terms like false-positive, true positive rate, and positive predictive value with respect to their work. This

6 The wake of Cold Case Project’s path leaves the latter notion unequivocal.
is particularly important in terms of assessing the accuracy of a model. As we questioned in our previous article, if the idea is to find the proverbial needle in the haystack, how useful is a model that simply scoops up all the hay and celebrates the fact that, in doing so, it also found the needle? That is not predictive analytics, that is unadulterated marketing. Models that help us minimize the hay through which we need to sift and maximize the needles that we are able to find are what may actually be useful. Even more, child welfare professionals need to be skeptical consumers of predictive analytics, demanding transparency in how predictive algorithms are developed and implemented. As we discussed in our article, while proprietary concerns of developers are important considerations, they must take a back seat to ethical and due process concerns of vulnerable families involuntarily interacting with government actors. This is important because if a model cannot reveal to child welfare professionals why it is producing the output that it is producing, then the model has no place in the system. Finally, it is important for predictive models in child welfare to be developed in a way that enhances, not supplants, professional intuition. In the absence of scaffolding, a predictive model that reduces the complex interactions of humans to a numerical risk score is devoid of utility. (Church & Fairchild, 2017)

This article adds additional prerequisites for developing predictive models and for using their outputs in child welfare that continue to scrutinize the appropriate ethical, moral, and legal framework for their use. Predictive analytics in child welfare must be conceptualized only as a component part of a multi-step process to develop and to refine the system through which we interact with children and families. Precise identification of an outcome that we either strive to promote or hope to avoid is a necessary, but not sufficient, step in this process. As we discussed in our article, the accuracy of a predictive model cannot be untethered from the responsive action needed to utilize the algorithm's output (Church & Fairchild, 2017).

Consider a predictive model that combs through administrative data during intake to assign a numerical risk score to a family. Of course, that score must be an accurate assessment of risk to be useful (Church & Fairchild, 2017). Even so, a predictive model that accurately identifies risk, yet is untethered from a responsive action necessary to mitigate such risk, is flawed. When we use predictive analytics as a means to intercede and to offer up a status-quo array of services to unwilling participants, what the system describes as innovation could just as easily be described as a harmful experiment on our nation’s most vulnerable families. Why develop a complex and novel algorithm to identify Anthony if we have no confidence in our interventions to find children like Anthony a legal family?

Using predictive analytics to identify vulnerable populations in child welfare raises at least two separate considerations. First, if the predictions derive from allegations of maltreatment, then any proposed intervention must be an unequivocal benefit to the subjects of the allegation. Second, the intervention must be tailored to address whatever was predicted and effective in the very particular context of the subjects and allegations. Too often, CPS agencies do not provide such interventions (Bergman, 2010).
Consider a common intervention resulting from a predictive model’s output in child welfare: a CPS investigation. From the family’s vantage, this can hardly be perceived as a benefit. Moreover, the efficacy of this intervention is dubious (Bergman, 2010). It is a fragile causal link to believe a child welfare report involving a family with housing, food insecurity, or income insecurity will be addressed if a predictive model flags a case and the ensuing intervention is a CPS investigation. Would we so blithely encourage hospitals to treat all sick patients with a medication before making a proper diagnosis? What if the model unveiled the most important and actionable causal interactions that contributed to the risk rather than just a numerical score? And what if the response to the findings was not a CPS investigation, but a referral to a civil legal aid attorney with experience in public benefits and housing, and more importantly, an ethical duty of loyalty to the family (ABA, 2018)? What if the response mirrored an increasingly common response in health care, using social workers to refer families to community resources?

While a CPS investigator arguably could make the same referrals when conducting an investigation, their primary job is to determine whether the child was a victim of abuse or neglect. Contrast that with a hospital social worker whose primary concern is the family’s health. Such professionals may also be better equipped to address the underlying issues of a CPS referral. Generally speaking, various state and non-profit actors - public health professionals, mental health professionals, civil legal aid lawyers - would have different approaches to address the factors that lead to a CPS report, each of which might be effective in particular circumstances that the analytics can unveil.

Integrating predictive analytics into child welfare is not as simple as procuring models that accurately identify an output of interest using statistics and data. Rather, a critical component of integrating predictive analytics responsibly in this context is the careful consideration of what the system does with the output. If we can identify the risk, then we next must carefully consider the system’s responsive action.

This article thus far has admittedly left little room for predictive analytics in child welfare absent a radical transformation of child welfare interventions. However, there is still a place for predictive analytics in our current system. Child welfare could use predictive analytics to identify our own deficits rather than those of the families we aim to serve. This is where CCP got it right. The model produced a list of children that had been in foster care for at least two years, ranked according to the likelihood that they would not achieve permanency before they reached the age of majority. Most of these children had spent years in foster care, in the custody of the State, and in the homes of strangers paid by the State to care for them. In Anthony’s case, that was 17 unfamiliar places. Although it took discipline, the focus of CCP was stubbornly child-centered and trauma-informed: the question was always “how could we have let this happen?” CCP remains intolerant to considering whether the child’s behavior or choices could have contributed to his or her lack of permanency.

This type of self-reflection requires a transformation from a passive to a proactive approach. Industries with a culture of safety embrace this type of action. For example, the airline
and healthcare industries constantly self-reflect and examine internal processes with the 
express aims of improving client/patient safety and minimizing errors or mistakes. There are 
even direct analogs in retail marketing. Consider that rather than pushing the same products to 
everyone who lands on a particular page, Amazon combs through their data to improve their 
confidence that if they put a particular product with particular characteristics on a certain page at 
a certain time, a particular individual consumer is more likely to purchase it. Child welfare could 
use predictive analytics to tailor efforts to better serve children and families, as opposed to using 
predictive analytics to simply identify a set of interactions that characterize broad swaths of 
families to whom we offer up cookie-cutter services or resources.

In a field hyper-focused on assessing risk, is it such a stretch to consider the risk of harm 
caused by our own interventions? There is no shortage of examples where the child welfare 
system has caused harm, though data suggest this is the exception rather than the rule. A 
predictive model working in concert with staff that insist on self-reflection and focus on 
interventions that provide unequivocal benefits to families side-steps the ethical, legal, and 
moral quagmires that haunt the intersection of predictive analytics and vulnerable populations.

Certain child welfare interventions certainly harmed Anthony. At the time of CCP review, 
Anthony had experienced 17 placement changes, more than two-thirds of which were 
unanticipated changes that likely compounded his trauma. He was living in an institution over an 
hour away from his community. Anthony repeatedly asked to be able to visit with his older sister, 
now an adult living in his hometown. But that plan was deemed unsafe: there was too much risk 
Anthony would go AWOL. He went AWOL anyway. As mentioned above, it was not the first time 
that Anthony had run away from foster care, but it was his last.

Fast forward to a runway in Atlanta, GA on August 11, 2016. A CCP staff member was 
on a plane, in an extended ground-hold. The pilot told passengers they could use their phones 
while she waited for clearance to get back in line for take-off. The staff member turned on his 
phone and saw a text message: they found Anthony. While frantically making phone calls, he 
learned Anthony had been arrested and charged with first-degree murder. When asked later in 
court about what the CCP staff member did next, he told the Court: “I did exactly what I would 
have done if this was a call concerning my child: tried to get him the best lawyer in town.”

The solicitor did not prevail on the capital murder charge at trial, but Anthony did plead 
guilty to stealing a car. The system responsible for protecting Anthony during his childhood 
failed him time and time again. It was only when another state agency tried this child as an adult 
for a heinous crime that some of the most competent professionals in the state became 
concerned with his past, present, and future well-being.

It was at this moment that Anthony found his first fearless champion. Anthony, who 
maintained his innocence, was represented by one of the most prestigious lawyers in town. This 
lawyer agreed to represent Anthony in exchange for a five dollar retainer. Over the next year, 
Anthony’s legal permanency plan changed from adoption to relative custody, with the plan now 
to discharge Anthony to the same sister they previously refused to consider for even visitation.
What a bitter irony: the system was only willing to take a risk on a different course of action once Anthony was incarcerated, so that it meant they could wash their hands of him in the event he was released.

Predictive analytics accurately identified Anthony. In this article, we described how CCP tried to use that identification to help him. Central to their efforts was a constant self-reflection on how the system had failed Anthony, and what could be done to avoid further harm. The result, however, reflected a better-than-most intervention that still wasn’t enough to overcome a rigid bureaucracy. Over-reliance on predictive algorithms and oversimplification of their findings undermines much of the promise that they hold. Machines lack moral consciousness, so it will not be the machines that force self-reflection in a system that can traumatize, overlook, and ultimately fail a child like Anthony. Rather, humans must use the output of algorithms to match powerful, evidence-based interventions to families that have identified needs. Only self-disciplined in this way do we inch closer to an ethically, morally, and legally sound framework for using predictive analytics in child welfare.

Citations


