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Discussion

Risk assessment and decision making in child protective services: Predictive risk modeling in context

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ABSTRACT

In an era in which child protective service agencies face increased demands on their time and in an environment of stable or shrinking resources, great interest exists in improving risk assessment and decision support. In this article, we review the literature and provide a context for predictive risk modeling in the current risk assessment paradigm in child protective services. We describe how predictive analytics or predictive risk modeling using linked administrative data may provide a useful complement to current approaches. We argue that leveraging technology and using existing data to improve initial triage and assessment decisions will enable caseworkers to focus on what they do best: engaging families and providing needed services.

1. Introduction

In 2014, the U.S. child protective services (CPS) system received 3.6 million allegations of child abuse and neglect, involving an estimated 6.6 million children. Of these, approximately 3.2 million children experienced an investigation or received an alternative response and an estimated 702,000 were found to have been victims of abuse or neglect. From there, 21% (n = 147,462) entered foster care (U.S. Department of Health and Human Services, 2016). Thus, every day through a series of decisions often made by multiple individuals, children and families are referred to CPS and then triaged. Yet a comprehensive understanding of how most effectively to screen and then serve children and their families is still emerging. Correctly ascertaining levels of acute and chronic maltreatment risk among the millions of children referred to CPS agencies each year is no easy task, nor is matching and tailoring services to meet the needs of these children and families.

The risk factors for child maltreatment have been well documented for decades. Multiple individual, family, and community risks are often present for these vulnerable children, including poverty (Gil, 1971; Jones & McCurdy, 1992; Pelton, 1989, 1994; Sedlak & Broadhurst, 1996; Wolock & Horowitz, 1979) and its many correlates, such as female-headed families (Brown, Cohen, Johnson, & Salzinger, 1998; Gelles, 1989, 1992; Gillham et al., 1998; Sedlak & Broadhurst, 1996), low parental education (Brown et al., 1998; Kotch et al., 1995; Zuravin & DiBlasio, 1996; Zuravin & Grief, 1989), unemployment (Gelles, 1989; Gillham et al., 1998; Kotch et al., 1995), welfare receipt (Brown et al., 1998; Jones & McCurdy, 1992; Needell, Cuccaro-Alamin, Brookhart, & Lee, 1999; Paxson & Waldfogel, 2002), and impoverished neighborhoods (Coulton, Crampton, Irwin, Spilsbury, & Korbin, 2007; Coulton, Korbin, Su, & Chow, 1995; Drake & Pandey, 1996).

Characteristics observable and universally collected at the time of birth also have been documented as related to risk of CPS referral, including early maternal age, late or absent prenatal care, low birth weight, birth abnormalities, and positive toxicology (Hussey, Chang, & Kotch, 2006; Putnam-Hornstein & Needell, 2011; Stith et al., 2009). Higher rates of CPS reporting also have been found among Black and Native American children relative to their White and Hispanic counterparts (Ards, Myers, Malkis, Sugrue, & Zhou, 2003; Drake, Lee, & Jonson-Reid, 2009; Font, Berger, & Slack, 2012; Putnam-Hornstein & Needell, 2011). Although child maltreatment is found disproportionately among non-White and teen-parent families, considerable evidence suggests that socioeconomic status also may confound these relationships because minorities and adolescent parents are disproportionately likely to be single and poor (Bolton, Laner, & Kane, 1980; Garfinkel & McLanahan, 1986; Gil, 1971; Kinard & Klerman, 1980; Saunders, Nelson, & Landsman, 1993).

Despite the wealth of literature regarding risk factors for child maltreatment, the accurate identification of referred children for whom the threat of maltreatment is most immediate and consequential has proven difficult. High rates of subsequent maltreatment referrals among children with initially unfounded allegations (Drake, 1996; Fluke, Shusterman, Hollinshead, & Yuan, 2005; Jonson-Reid, Drake, Chung, & Way, 2003) and increased risk of child maltreatment deaths

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despite CPS involvement (Barth & Blackwell, 1998; Jonson-Reid, Chance, & Drake, 2007; Putnam-Hornstein, 2011; Putnam-Hornstein, Cleves, Licht, & Needell, 2013; Sabotta & Davis, 1992; Sorenson & Peterson, 1994) point to the enduring struggle to accurately assess children's current and future risk of abuse and neglect.

For nearly three decades, risk assessment tools have been employed in CPS to help improve the accuracy of workers' frontline decision making. Although these tools are generally considered more effective than clinical attempts to weight the complex factors associated with a child's risk of harm, there are numerous operational and statistical limitations to such operator-driven assessments. These include: (a) questionable tool implementation fidelity; (b) the time and expense of using these tools on repeated occasions; (c) the absence of tool validation for the populations to which they are administered; (d) overreliance on static or historical risk factors; (e) limited predictive accuracy; and (f) a crude stratification of risk based on arbitrary thresholds (e.g., low, medium, high).

In short, the success of operator-driven risk assessment tools in the world of child protection relies on a frontline worker who is adequately trained and motivated to properly employ them (which is, at least anecdotally, a notable barrier in organizations) and who has the time to administer the tool in a fashion such that new data are incorporated into the risk or safety assessment. Importantly, the value of risk assessment tools are also premised on their utility—specifically their ability to influence decision making to facilitate better outcomes for children (D'Andrade, Benton, & Austin, 2005; Russell, 2015).

In this article, we review the strengths and weaknesses of the current risk assessment paradigm in CPS practice. We then describe predictive analytics or predictive risk modeling (PRM) using linked administrative data as an alternative method of prospective risk assessment that may help overcome many of the shortcomings of current approaches. In an era in which child protective service agencies face increased demands on their time and in an environment of stable or shrinking resources, great interest exists in improving risk assessment and decision support. We argue that leveraging technology and using existing data to improve initial triage and assessment decisions will enable caseworkers focus on what they do best: engaging families and providing needed services.

2. Risk assessment in child protection

The accurate assessment of child safety and risk is foundational to effective CPS practice (Gambrill & Shlonsky, 2000; Gelles & Kim, 2013; Rycus & Hughes, 2003). The inaccurate identification of risk can have significant implications for children and families that come into contact with the CPS system (Gambrill & Shlonsky, 2000; Shlonsky & Wagner, 2005). For instance, children and families misidentified as low risk may not receive necessary preventive services and may go on to experience abuse and neglect. Conversely, those misidentified as high risk may be subjected to unnecessary involvement with social services, disruption of the family environment, and loss of family autonomy (Gambrill & Shlonsky, 2000).

Risk assessment in CPS is largely a human enterprise. Clinical judgment or naturalistic decision making (Kahneman & Klein, 2009), however, has been shown to be prone to both human error and bias. Practitioners have difficulty processing large amounts of available information and often used flawed heuristic strategies instead of rational models. Practitioners' personal beliefs and biases and the culture of the agency can also affect assessment (Ægisdóttir et al., 2006; Dawes, Faust, & Meehl, 1989; Kahneman, Slovic, & Tversky, 1982; Kahneman & Tversky, 1973; Meehl, 1954; Nisbett & Ross, 1980). Given the well-documented limitations of clinical judgment, standardized risk assessment tools have been developed to help improve the accuracy of predictions of maltreatment recurrence (Rycus & Hughes, 2003; Shlonsky & Wagner, 2005). These tools combine risk factors related to child maltreatment risk to provide decision support to practitioners, and have proliferated during the last 30 years (Child Welfare League of America [CWLA], 2005).

2.1. Standardized tools

Two general categories of tools have been developed in an effort to help standardize CPS risk and safety assessments—theoretical or consensus-based and actuarial tools (Baird, Wagner, Healy, & Johnson, 1999; English & Pecora, 1994). Theoretical or consensus-based tools are typically guided by a theoretical approach and examine child maltreatment risk factors identified by experts through clinical experience or research. These risk factors are often combined into an instrument or scale that can assist practitioners with information gathering during assessment. Clinicians use these data to help determine recidivism risk. Despite their utility, such tools are often criticized as less precise, subjective, and inconsistent (D'Andrade et al., 2005).

Actuarial tools examine risk factors that are empirically related to child maltreatment and they are typically validated statistically (CWLA, 2005; Gambrill & Shlonsky, 2000; Shlonsky & Wagner, 2005). Unlike theoretical or consensus-based tools, actuarial tools can incorporate risk factors not theoretically related to abuse and neglect. When these tools are administered, weights are given to specific factors and combined into scales, resulting in specific probability estimates for recurrence risk. Actuarial tools are often criticized for failing to take into account the role of expert clinical judgment or causal theories (Grove & Meehl, 1996; Schwalbe, 2004). Additionally, they may ignore the role of services or other strengths in mitigating risk (D'Andrade et al., 2005).

Today, both categories of standardized risk assessment tools are considered more accurate than clinical judgment alone in predicting the recurrence of child maltreatment (Dawes et al., 1989; DePanfilis & Girvin, 2005; Grove & Meehl, 1996; Grove, Zald, Lebow, Snitz, & Nelson, 2000; Johnson & L'Esperance, 1984; Munro, 1999; Shlonsky & Friend, 2007; Shlonsky & Wagner, 2005). As a result, during the past two decades, the majority of state CPS agencies have adopted standardized risk assessment tools. A 2011 national survey conducted by Casey Family Programs found that the most widely used tools included Structured Decision Making (SDM) from the National Center on Crime and Delinquency (NCCD), the ACTION for Child Protection and National Resource Center for Child Protective Services model, and the Signs of Safety model (Casey Family Programs, 2011; Harbert & Tucker-Tatlow, 2012).

2.2. Standardized tool performance

Among standardized tools, actuarial models have generally been shown to be more effective than theoretical or consensus-based models in predicting child maltreatment recurrence (Baird & Wagner, 2000; Baird et al., 1999; Begle, Dumas, & Hanson, 2010; D'Andrade et al., 2005). In 2005, the Bay Area Social Services Consortium conducted a structured performance review of the five most widely used tools[1] for determining recurrence of abuse and neglect (D'Andrade et al., 2005). Five areas of instrument performance were assessed: predictive and convergent validity, interrater reliability, outcomes, and racial and ethnic group differences. Findings suggested that actuarial tools had greater predictive validity and interrater reliability than consensus-based tools in each area. Overall, the authors concluded that the implementation of actuarial tools has improved the accuracy of workers' risk assessment.

The actuarial tool most widely used today is the SDM system developed by the NCCD. The SDM system includes 10 decision support

[1] These include (a) the Washington Risk Assessment Matrix; (b) the California Family Assessment Factor Analysis (or the “Fresno” model); (c) the Child at Risk Field System; (d) the Child Emergency Response Assessment Protocol; and (e) the actuarial risk assessment instruments developed by the Children's Research Center.

tools that cover case decision making from hotline call to reunification. SDM system goals include improved assessments, increased consistency and accuracy in assessment, and increased efficiency in operations (NCCD, 2012). Selection of risk factors included in SDM risk scales is based on analysis of historical data. These actuarial scales and clinical assessments are combined in a decision matrix that helps determine risk of recurrence and probability of successful reunification. Thus whereas actuarial methods are relied on for risk factor selection, the SDM approach might be better termed clinically adjusted actuarial predictions, because clinical judgment can be used to adjust final risk scores (CWLA, 2005; Shlonsky & Wagner, 2005). SDM is currently in use in more than 20 states and several countries (NCCD, 2014). Several studies have confirmed the validity of the SDM risk assessment factors when predicting recurrence of maltreatment (Johnson & Wagner, 2003; Johnson, 2011; Wood, 1997).

Despite their widespread implementation, actuarial tools still have multiple operational limitations (D'Andrade et al., 2005; Gambrill & Shlonsky, 2000; Lyle & Graham, 2000; Wald & Woolverton, 1990). Although they are typically easier to score and interpret, these assessment tools are still prone to operator error in both application and interpretation. This lack of tool fidelity can compromise effectiveness. Additionally, actuarial instruments often contain subjective measures that require clinical judgment to score, such as determinations of whether adequate supervision is provided in the home. These items have been shown to be less reliable than more objective and well-defined variables such as whether previous maltreatment occurred and may affect predictive validity (D'Andrade et al., 2005; English & Graham, 2000).

Workers' differential interpretations of case histories can also result in inconsistent tool scoring. Several studies have demonstrated that different workers given identical case histories often make different case screening decisions (Britner & Mossler, 2002; Jergeby & Soydan, 2002; Rossi, Schuerman, & Budde, 1996). Studies have also shown that tools are often not used as intended by developers and often have little effect on workers' case-related behavior (Baumann, Law, Sheets, Reid, & Graham, 2005; Gillingham & Humphreys, 2010). For instance, caseworkers have been shown to ignore risk scores because they perceive them to overestimate risk and oversimplify the complexity of child welfare cases (Gillingham & Humphreys, 2010). Finally, operator-driven actuarial risk assessments are also resource intensive, requiring both staff time and funds for repeat administration and adequate education and training. These operational limitations are magnified in agency environments characterized by scarce resources, as well as large caseloads and high staff turnover rates.

Statistical limitations can also affect the effectiveness of actuarial assessment tools. Specifically, such tools are rarely normed to or validated with the population to which they are ultimately applied, resulting in static models of risk. Risk, however, is inherently dynamic; not only can risk levels change throughout the life of a case, but the profile of a service population can also change over time due to demographic shifts or changes resulting from agency initiatives (Boer, Hart, Kropp, & Webster, 1997; Sjöstedt & Grann, 2002). Actuarial models that rely on static historical associations fail to capture such changes. Additionally, many rely on crude stratification of risk based on arbitrary thresholds (e.g., low, medium, high) that limit their utility and decrease accuracy. Workers rarely receive detailed guidance on how best to prioritize families for attention in each risk category, further diluting the assessment tool's usefulness in practice. Finally, although some actuarial approaches use computational techniques for decision support, in general the field has not kept pace with rapid advances in technology and statistical modeling that can employ vast amounts of available data in the prediction of risk (Schwartz, Kaufman, & Schwartz, 2004).

Although a majority of investigations have shown higher predictive validity and reliability for actuarial models, several analyses have shown theoretical and empirically guided tools to have higher predictive validity than pure actuarial tools (English, Marshall, Brummel, & Coghlan, 1998). Some studies have also shown actuarial models to have high margins of error (Baumann et al., 2005; Camasso & Jagannathan, 2000). Critics have argued that when used to predict individual risk, pure actuarial models often fail to account for localized contextual or individual protective factors that interact to mitigate or enhance risk (Crea, 2010). Some argue that pure actuarial tools do not reflect the complex ecology of child maltreatment (CWLA, 2005; Gillingham & Humphreys, 2010).

Although experts in CPS risk assessment now generally agree that actuarial tools are more effective in predicting risk of child maltreatment than clinical judgment alone, these tools cannot and should not replace sound clinical judgment during the assessment process (Grove & Meehl, 1996; Knoke & Trocmé, 2005; Shlonsky & Wagner, 2005). Overreliance on resource intensive actuarial assessments can result in agency cultures dominated by procedural compliance that stifles the development of professional expertise (Munro, 2010, 2011a, 2011b). Even when actuarial tools are used appropriately for decision support, their usefulness is contingent upon the quality of the information available. In short, the success of these tools is dependent on a frontline CPS worker who is adequately trained and motivated to properly use the tool (anecdotally a notable barrier in CPS organizations) and who has the time to administer it in a fashion such that new data are incorporated into the risk or safety assessment (D'Andrade et al., 2005; Russell, 2015; Vaithianathan et al., 2012). Technological and computational advances have made it possible to overcome many of the shortcomings in the current child maltreatment risk assessment paradigm (Schwartz et al., 2004). One of the most compelling of these is PRM.

3. Predictive risk modeling

Many of the operational and statistical limitations of traditional actuarial risk assessment tools can be addressed with the application of predictive analytics. Predictive analytics refers to the application of data mining, modeling, and analytic techniques to existing data to discover patterns and make predictions (Guazzelli, 2012). PRM, a type of predictive analytics, is a statistical method of identifying characteristics that risk-stratify individuals in a population based on the likelihood each individual will experience a specific outcome or event. The result of the model's mathematical algorithm is a risk score. Unlike model-building techniques traditionally used in risk assessment—in which variables are chosen on the basis of previously researched relationships with the specified outcome—in PRM, as many data points as possible are examined, even if there is no previously specified relationship with the outcome of interest.

This technique has several advantages relative to other actuarial methods of risk assessment. First, because PRM uses vast amount of data, it can identify previously unobserved relationships between variables (Marshall & English, 2000). Second, PRM models are learning models that can continually adjust to new relationships present in the data. This flexibility allows the models to account for variants in different subpopulations and capture dynamic changes in risk over time. Third, PRM models use existing data on the population for which the tool is being used, whereas more common actuarial instruments are rarely validated with the population of interest (Russell, 2015). Fourth, PRM as an approach is inherently more consistent than other risk assessment procedures. Variable selection, although limited by available data, is mathematical and there is no arbitrary selection of predictors. Fifth, unlike typical operator-driven assessments—in which effective implementation is dependent on worker training and compliance—PRM models operate independent of such factors (Vaithianathan et al., 2012).

PRM is used in many industries for decision support and targeting of interventions, including insurance, credit, marketing, and health care (Liao, Chu, & Hsiao, 2012; Tsai, 2012). Insurance uses include claims management, fraudulent claims detection, reserve setting, underwriting, and retail marketing campaigns (Nyce, 2007). The technique is also routinely used by the U.S. government to detect fraud. For instance, the Center for Program Integrity, a division of the Centers for Medicare & Medicaid Services, uses real-time predictive analytics to detect both beneficiary and provider claim fraud. Algorithms produce risk scores and high-risk claims are flagged for review by trained claims analysts (U.S. Department of Health and Human Services, 2011). Predictive analytics has also been deployed successfully for many years for fraud detection in the credit card industry (Ngai, Hu, Wong, Chen, & Sun, 2011). In the e-commerce sector, marketers and businesses use data-mining techniques to predict buying patterns and help target personalized advertising (Berry & Linoff, 2004).

Predictive models were initially implemented in health care settings decades ago as a strategy for managing costs—specifically to deal with the small proportion of patients that accounts for a large share of the costs (Axelrod & Vogel, 2003; Cousins, Shickle, & Bander, 2004; Panattoni, Vaithianathan, Ashton, & Lewis, 2011). Subsequently, PRM has been used successfully to predict risk of heart failure, lung cancer, breast cancer, post-surgery mortality, and emergency department use (Brennan, Dieterich, & Ehret, 2009; Euhus, 2004; Fogel, Wasson, Boughton, & Porto, 1998; Kanazawa, Kubo, & Niki, 1996; Lewis et al., 2013; Moore, Gerdtz, Hepworth, & Manias, 2011; Moore et al., 2012; Orr, 1997). Automated models are also used routinely in health care to provide decision support.

The application of predictive analytics in health care has evolved to where it is now being used to personalize medical interventions for individual patients (Brooks, 2013). For instance, in 2010, the U.S. Department of Health and Human Services implemented a framework to employ PRM to appropriately identify and stratify high-risk patient populations, particularly patients with multiple chronic conditions for more focused care intervention (Weir & Jones, 2009). In addition to health care, predictive analytics has been used to improve assessment in the social services arena. For example, researchers have used PRM to predict homelessness recidivism and to more efficiently target services (Shinn, Greer, Bainbridge, Kwon, & Zuiderveen, 2013; Shinn et al., 1998).

4. PRM in child protection

Despite its proven utility in many fields, PRM has only recently been applied to the classification of risk in CPS. Several national and regional efforts are underway to examine its efficacy in this area. Although these initiatives differ in scale and purpose, most are using predictive analytics to help identify families and children at risk and triage them for preventive services. Packard (2016) reviewed the implementation of PRM in CPS to date and found that it has been used to predict risk of maltreatment, recurrence, child death, failed reunifications, and youth resilience, among others. For our purposes, several recent projects focused on predicting child maltreatment risk and recurrence are worth highlighting.

Early work by Marshall and English (2000) and Zandi (2000) used artificial neural networks to predict child abuse risk. Marshall and English (2000) used administrative data from Washington state's CPS risk assessment data to successfully model workers' risk assessments using 37 risk factors. The neural networks were found to be more effective than other multivariate techniques (Marshall & English, 2000). Using data from the Third National Incidence Study of Child Abuse and Neglect, Zandi (2000) and Schwartz et al. (2004) experimented with using artificial neural networks to train a model to predict children's likelihood of meeting the study's harm standard. In both cases, the predictive risk models reliably predicted risk of abuse (Schwartz et al., 2004; Zandi, 2000).

Vaithianathan et al. (2012) used prospective population-based PRM to examine child maltreatment risk in a general population in New Zealand. The project used linked records from public work and income, child and family health, and welfare systems to predict maltreatment (substantiated finding of neglect or emotional, physical, or sexual abuse) by age 5 among children in New Zealand. The model, which used 132 predictors, accurately predicted maltreatment risk with an area under the receiver operating curve of 76%, a rate similar to that found in digital mammography (Vaithianathan et al., 2012).

The Florida Department of Children and Families and its technology vendor, Eckherd, used CPS data for a 5.5-year trend analysis of child fatalities. The analysis applied predictive analytics techniques to CPS hotline data identify the characteristics of children with higher odds of premature death (Florida Department of Children and Families, 2014). The analysis identified 14 risk factors associated with increased risk of child death, including age (children aged 0–2 were most at risk), prior removal for physical or sexual abuse, removal for parental substance abuse, and presence of a physical or intellectual disability. Receipt of in-home services was shown to have a protective effect.

The results of such studies have also been operationalized in CPS practice. For instance, in Florida's Hillsborough County, the Department of Children and Families has developed the Eckerd Rapid Safety Feedback tool (Eckerd, 2016; Florida Department of Children and Families, 2014). A qualitative review was used to identify risk factors associated with risk of child fatality. Using these factors, a real-time overlay for the county's automated child welfare information system was developed so that workers could monitor these specific factors using a dashboard and intervene to ensure child safety when warranted. In addition to focusing on child fatality, predictive analytic applications have been developed for other child welfare outcomes including re-abuse, long stays in foster care, aging out, and reentry following reunification, among others (Mindshare Technology, 2016). The Eckerd model is currently being investigated for use in other jurisdictions, including Connecticut, Alaska, Oklahoma, Nevada, and Maine (Heimpel, 2014).

Most recently, Allegheny County, Pennsylvania, has implemented a PRM tool in its CPS hotline known as the Allegheny Family Screening Tool. The tool uses data from 27 departments housed in the county's data warehouse. The PRM model produces a risk score, enabling hotline workers to determine if referrals should be screened in for investigation (Vaithianathan, Jiang, Maloney, & Putnam-Hornstein, 2016a, 2016b). Risk scores (ranging from 1 to 20) are assigned to the entire household, not just the child victim, indicating the likelihood of a placement or re-referral in the 365 days following the hotline call. Further work is currently underway to explore models that might be deployed further upstream, helping to prioritize families for various early intervention and family support programs. A key feature of PRM models is that they can be thought of as learning models, and when implemented in live data systems, risk scores are continually adjusted to take into account prior history and models are regularly re-weighted and re-validated.

5. Challenges of PRM

Earlier described projects illustrate the potential benefits of the implementation of PRM to risk assessment in CPS. By leveraging technology and existing administrative data, they are enabling agencies to overcome many of the shortcomings in the current risk assessment paradigm. Despite the exciting promise of PRM as a risk classification tool, there are many challenges to successful and proper implementation. These challenges can be operational, legal, and ethical.

5.1. Operational challenges

Despite the improved prediction capacity gained from the application of PRM, no model is 100% accurate. Determining a PRM model's risk threshold involves balancing the model's specificity and sensitivity (type I and type II errors), because the two are inversely related. Setting a high risk threshold increases a model's sensitivity, but also increases the proportion of false negative risk classifications (type II error).

Conversely, setting a low risk threshold will increase a model's specificity, but also increase the proportion of false positive risk classifications (type I error). As Baumann et al. (2005) notes, when child safety is concerned, model sensitivity may be prioritized and resulting higher false positive rates are tolerated.

These statistical decisions can have concrete consequences for children's lives. Specifically, children and families misidentified as low risk may not receive necessary preventive services and go on to experience abuse and neglect, whereas those misidentified as high risk may be subjected to unnecessary involvement with social services (de Haan & Connolly, 2014; Gambrill & Shlonsky, 2000). Misclassification errors, however, are not limited to PRM techniques; they are also possible with clinical judgment and other risk assessment strategies. The advantage of PRM compared with other strategies is transparency. As Dare and Gambrill (2016) argued, “the greater accuracy and transparency of predictive risk modeling tools also allows them to serve as (inevitably imperfect) checks against well-understood flaws in alternative approaches to risk assessment” (p. 4). The expertise of both clinicians who understand the practice implications of false positives and false negatives, as well as statisticians who can quantify trade-offs, is required to set initial risk thresholds. The ongoing involvement of both clinicians and statisticians is also required to analyze the performance of PRM models and appropriately re-weight covariate predictors and adjust thresholds to reflect changes in the client population and the local decision making context.

An additional operational concern for PRM relates to the selection of the outcome to be predicted. These models can be highly effective in predicting events that occur with sufficient frequency. Research however, has suggested that predictive models do not perform well when predicting less frequent rare events. It is critically important that agencies recognize these statistical limitations. With the best of intentions, some agencies are seeking to employ PRM to help prevent the worst and rarest of child protection outcomes: child fatalities (Florida Department of Children and Families, 2013). CPS leaders should be cautious because the analysis of rare events requires very special attention and current data-mining techniques are often insufficient for efficiently handling these extremely rare events (Lazarević, Srivastava, & Kumar, 2004).

Data availability and quality are also important operational concerns for PRM (Russell, 2015). The statistical power of PRM models improves with large amount of data. In addition to ensuring that adequate data are available, the quality of these data must be considered (Connelly, Playford, Gayle, & Dibben, 2016). Large amounts of missing data, poorly specified data fields, or data errors can affect model performance. In agencies, efforts must be made to demystify the PRM black box and the data fields it requires to promote buy-in and ownership by frontline data-entry staff members (Gillingham, 2016). Such efforts will ultimately improve data quality and model performance.

In addition to child abuse and neglect information systems, additional service data of interest includes: public assistance (i.e. TANF, WIC), education, health, mental health, developmental services, employment, housing, and criminal justice. These sources likely include useful predictors that might aid in the assessment of child safety. The range of data available for PRM, however, depends on location, and there is wide variability in the types and quality of data available across jurisdictions. In some locations, child welfare and other service system data can be found in integrated data bases. While in others, data remains siloed and utilization requires multiple data use agreements and time consuming data linkages.

5.2. Legal and ethical challenges

A variety of legal and ethical questions arise when PRM techniques are used to identify the recurrence risk of abuse and neglect. Dare and Gambrill (2016) pointed out that the ethical costs and benefits of PRM need to be compared with the next best available alternative, rather than some theoretical ideal. Because of the unfamiliar nature of PRM tools, they tend to be subjected to greater level of criticisms, many of which could equally be leveled at other operator-driven tools. The areas of concern include privacy and consent, potential discrimination, and proprietary ownership. When implementing PRM, privacy concerns regarding the use of public data to identify those at risk must be considered. For instance, does the concept of due process apply to families and their risk scores? How is consent to information granted? (Christian, 2015; Dare, 2013, 2015; Dare & Gambrill, 2016). These needs for privacy and due process must be balanced with the agencies' duty to ensure the safety of children. In their review of the Allegheny County project, Dare and Gambrill (2016) acknowledged that privacy and consent must be given consideration when PRM techniques are applied. However, they argued that PRM and other modeling techniques simply represent a more efficient way of using existing agency data for risk assessment. “The model does not create new rights of access to that information—that a diligent child protection official would already have been entitled to gather the information now to be accessed by the tool” (Dare & Gambrill, 2016, p. 3).

An important ethical concern is whether PRM techniques will exacerbate already prevalent racial disparities in CPS. Specifically, if agency data reflect persistent racial bias, then misclassification errors and their consequences might result. Although this possibility is inherent in PRM, proponents have noted that models provide an opportunity to openly and systematically track disparities and correct for them, which is difficult to do with alternative approaches (Dare & Gambrill, 2016).

A final ethical concern relates to the logistics of PRM itself. In an effort to improve practice, many jurisdictions have embarked on PRM initiatives. Although CPS data are based in public agencies, because of the statistical expertise required, model development is often contracted to private, for-profit vendors. Although PRM models are mathematically transparent, when private vendors are involved, intellectual property laws often apply, and therefore the “details of model development, performance metrics, and statistical methodologies” (Russell, 2015, p. 188) required to validate accuracy and utility may not be available. Child welfare leaders have the responsibility to continue be critical consumers of information and ensure that the validity and reliability of models are examined on an ongoing basis (Russell, 2015). In addition to these measures, agencies can promote intra and inter agency transparency through the formation of advisory panels, the establishment of clear implementation guidelines, the public release of model input and performance details, and the solicitation of external reviews.

Ultimately, the effective use of PRM techniques demands agencies have well-developed protocols for intervention when risk is determined. To be effective, any risk assessment system must be efficient and simple to administer, the agency culture must fully support implementation, leaders should understand the basics of the model, and workers and supervisors must buy in to the new classification system. Such systems, however, are not an end game; rather as O'Brien (2015) stated, “jurisdictions must be prepared to take action, otherwise they are engaging in a strictly academic exercise” (p. 6). Even if prediction algorithms can identify at-risk clients, intervening to change the outcome may be limited. Improving outcomes ultimately depends on the willingness of families identified through PRM to accept services and the quality of the services delivered.

6. Conclusion

Predictive analytics offer much promise to the field of child protection as a classification and risk stratification tool. Although there are important operational, legal, and ethical considerations in the application of PRM for this purpose, there also exists both a fiscal and ethical imperative to leverage scarce resources to assist those families most in need. Available evidence demonstrates that predictive risk models, when employed in combination with careful clinical practice (Crea, 2010; Shlonsky & Wagner, 2005), can satisfy this imperative responsibly, ethnically, and effectively. Still, much is unknown and great caution must be exercised and thought given to implementation (Zullinger, 2015).

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