PREDICTIVE RISK MODELING: PRACTICAL CONSIDERATIONS

Children's Data Network

The increased availability and improved quality of administrative data have sparked interest in data analytics for risk stratification and case management purposes. Predictive risk modeling (PRM) is one such class of tools. In PRM, algorithms are used to generate a score for individuals in a given data system reflecting the probability or risk of one or more adverse outcomes. Because predictive risk models are built and run using information that has already been collected, these tools allow large populations to be quickly, easily and cost-effectively stratified by risk.

Risk stratification allows our services systems to better match resources (e.g., staff time,service slots) to the needs of what may be very different subpopulations. For higher-risk and higher-need subpopulations, more intense and longer duration services can be delivered with the objective of ensuring an adverse outcome is avoided. For medium-risk and medium-need populations, intervention goals can include enhancing protective factors and reducing the effects of cumulative risk. Finally, for low-risk and low-need populations, universal support services may be sufficient.

PRM requires: (1) comprehensive and updated administrative data on risk factors correlated with the event one is trying to predict and then prevent; (2) risk-scoring algorithms that are accurate and can be deployed in advance of the adverse event; and (3) effective and adequately resourced service interventions for individuals who are identified as at risk of negative outcomes.

In health care settings, the use of PRM reflects a growing appreciation that many patients have a multiplicity of risk factors and conditions – and its use is generally uncontentious. For example, the use of PRM to target supportive case-management services to patients with a heightened risk of re-hospitalization is generally viewed as acceptable. And from aclinical perspective, PRM helps medical professionals avoid an overly narrow focus on the acute condition for which an individual is being treated, without proper awareness or weighting of other factors that may contribute to patient outcomes. The same challenges that confront health care providers in identifying high-risk versus low-risk patients are also present in child welfare systems. Yet, while PRM holds promise as applied to varying levels of maltreatment prevention, its use also presents unique and challenging considerations.

From a primary prevention standpoint, maltreatment risk screening at a population level may support the strategic prioritization of children and families for early intervention services. In the context of secondary and tertiary maltreatment prevention, PRM may enhance child protection (and family strengthening) through improved assessments and more empirical tailoring of services to needs.

The use of information and statistical models to identify children at risk of maltreatment before any abuse or neglect has occurred, or as a tool for screening families reported to child protection hotlines, is much more complex. Beyond very legitimate concerns that such tools might reinforce historical biases (especially by race and class), the precision of a given model must also feature into assessments of its potential for good versus harm. And any tool is only as good as its implementation and buy-in from the child welfare workforce.

Discussions of PRM in the field of child welfare are in some respects new – but ultimately build on decades of research and efforts to standardize and improve decision-making.

PRM has the potential to generate information valuable to accurately, efficiently and fairly screening allegations of abuse or neglect so that children most in need of services and support get them. But our communities should not take that for granted. Toward that end, we believe that there are several important early "lessons" from the field that should guide jurisdictions exploring PRM. (And we trust that this list will grow!)

1. ***Openness and transparency should be the rule, not the exception. The goal should be to develop a glass box rather than a black box.***

2. ***The software needed to deploy a model may be proprietary, but the actual model need not be. Public agencies, not vendors, should own model code and weights.***

3. ***View skeptically anyone trying to sell a "secret sauce." The independent validation of model performance and independent evaluation of its implementation and impact should be features of all initial PRM efforts.***

4. ***Race matters. Model accuracy should be assessed for children of different races/ethnicities and unwarranted disparities should be addressed.***

5. ***Community engagement and input is critical. Communities should demand (and receive) information concerning how the model is being used and how the model performs.***

6. ***PRM should be initially implemented to augment and complement clinical judgementand other approaches to assessment – not as a substitute.***

7. ***Once implemented, models can and should be re-weighted and re-validated on an ongoingbasis in order to maintain accuracy.***

8. ***There will be diminishing returns to improvements in classification accuracy as more and more data sources are added. Cross-sector data are not a prerequisite to developing a model that supports improved decision-making.***

We should not look to PRM as a silver-bullet. Like any tool, it has its limitations. But we can either continue with practice as usual out of fear of the new and different (and a desire for something perfect), or we can openly and transparently explore opportunities to equip our child welfare workforce with information that, on the margin, may improve child safety.

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