Children in the Public Benefit System at Risk of Maltreatment

Identification Via Predictive Modeling

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Abstract: A growing body of research links child abuse and neglect to a range of negative short- and long-term health outcomes. Determining a child's risk of maltreatment at or shortly after birth provides an opportunity for the delivery of targeted prevention services. This study presents findings from a predictive risk model (PRM) developed to estimate the likelihood of substantiated maltreatment among children enrolled in New Zealand's public benefit system. The objective was to explore the potential use of administrative data for targeting prevention and early intervention services to children and families.

A data set of integrated public benefit and child protection records for children born in New Zealand between January 1, 2003, and June 1, 2006, was used to develop a risk algorithm using stepwise probit modeling. Data were analyzed in 2012. The final model included 132 variables and produced an area under the receiver operating characteristic curve of 76%. Among children in the top decile of risk, 47.8% had been substantiated for maltreatment by age 5 years. Of all children substantiated for maltreatment by age 5 years, 83% had been enrolled in the public benefit system before age 2 years. This analysis demonstrates that PRMs can be used to generate risk scores for substantiated maltreatment. Although a PRM cannot replace more-comprehensive clinical assessments of abuse and neglect risk, this approach provides a simple and cost-effective method of targeting early prevention services.
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Introduction

Child maltreatment is an international public health problem, the scope and consequences of which are increasingly recognized.[1–3] It is estimated that 40 million children worldwide are the victims of abuse and neglect annually.[4] Yet, despite a range of policy initiatives since the inception of modern child protection services (CPS) in the 1970s, countries have struggled to develop successful maltreatment prevention and intervention strategies.[5,6] A recent analysis of data from New Zealand, the U.S., and four other developed nations suggested wide variations in the degree to which CPS intervened with children and families, despite small differences in the rates of violent death or maltreatment-related injuries, two indicators of the successful protection of children.[7]

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Child protection efforts are complicated by the challenge of accurately assessing a child's future risk of maltreatment. Victims are frequently born into complex family environments with many risks,[1,3,8,9] yet no single factor deterministically predicts maltreatment. Nonetheless, correctly assessing the likelihood that a child will be the victim of future maltreatment would enable scarce resources to be strategically targeted. An array of evidence-based programs could be offered to families, with intensity and service levels tailored to maltreatment risk.[10,11]

Predictive risk modeling (PRM) is one approach to assessing an individual's future risk of an adverse event. PRM is most advanced in healthcare utilization,[12] but it has not been adopted as a tool for stratifying children based on future maltreatment risk. The principal requirements for the use of PRM include (1) a sufficiently broad segment of the target population captured in systems from which data can be harvested; (2) comprehensive and timely data on risk factors such that risk scores that can be generated in advance of an adverse outcome; and (3) outcomes that can be predicted with sufficient accuracy.[12] In the context of child maltreatment, it is also important that the protocols followed once the risk score is generated are both legal and ethical.

The current analysis tested whether a predictive risk model could be developed and validated as a tool for identifying children at high risk of substantiated maltreatment using administrative data. The model was designed to generate a risk score for every child enrolled in New Zealand's needs-based public benefit system before age 2 years. If implemented, the model would generate risk scores using a computerized algorithm, which would then trigger a targeted early intervention response with the aim of preventing maltreatment.

Methods

Data Set

This analysis relies on a unique data set constructed through record linkages between New Zealand's public benefit and child protection systems. These data were linked by the New Zealand Ministry of Social Development for research purposes. Data were matched using a probabilistic algorithm based on personal identifiers.[13] Linked data included 103,397 public benefit spells, reflecting 57,986 unique children.

For inclusion, the child had to be born between January 1, 2003, and June 1, 2006, and have had a spell in the benefit system between the start of the mother's pregnancy and age 2 years. "Spell" was defined here as a child's inclusion in a benefit case, and this was treated as the unit of analysis. Because many children have multiple benefit spells, and risk varies over time, the model generated a new risk score at each of the following time points: (1) the caregiver (s) registered for a new benefit; (2) there was a change to the type of benefit received; and (3) the benefit agency was notified of a change in the identities of the caregivers(s) associated with the child.

See related Commentary by Macchione et al. in this issue.

At the start of each new spell, all predictor variables were updated through administrative records. Data were provided to the research team in 2012 under confidentiality agreements with the University of Auckland. The university's ethics committee deemed that this project was exempt and did not require ethics approval, as the data were de-identified.

Variables

Outcome variables. The dependent variable was defined as a substantiated report of maltreatment. This outcome was dichotomously coded, reflecting whether each child had any substantiated reports of neglect, physical abuse, sexual abuse, or emotional maltreatment by age 5 years. The substantiation of a report means that the investigating social worker gathered clear and sufficient evidence to determine that maltreatment occurred.

Predictor variables. A total of 224 predictor variables were constructed based on information gleaned from the benefit and CPS data. Variables included both contemporaneous and historical information for children and caregivers. Nearly 45% of predictor variables related to the demographics, SES, and histories of the primary caregiver, whereas 37% related to the primary caregiver's partner (present in 28.9% of spells). To address missing variables when no partner was present at the beginning of a spell, a partner indicator variable (0/1) was created and then interacted with the full set of partner variables. This meant that the predictive risk model included partner characteristics as predictor variables whenever a partner was present. The remaining 18% of predictor variables related to the characteristics of eligible children. Variables were chosen based on their availability in the data and their potential to proxy known risk and protective factors for abuse and neglect.

Data Analysis

The data were randomly split into a 70% prediction sample and a 30% validation sample, employing the methodology used by Billings et al.[12] The 70% prediction sample was used to estimate a stepwise probit model and the 30% validation sample to assess how well the model correctly identified children substantiated for maltreatment by age 5 years. In the stepwise approach, all 224 variables were used to predict maltreatment. A backward selection stepwise estimation command was used to eliminate variables that were not significant ($p>0.20$), or that were perfectly correlated. This relatively high p-value was chosen because of the potential for an artificial increase in the estimated SEs due to collinearity among predictors.

The final predictive risk model included 132 variables and was then used to predict substantiated maltreatment by age 5 years in the validation sample. The performance of the model was summarized by reporting the area under the receiver operating characteristic (ROC) curve and the 95% CI. ROC curves characterize the relationship between sensitivity and specificity. In this analysis, the sensitivity was the probability that a spell in which a child was substantiated for maltreatment was correctly identified by the model. The specificity was the probability that a spell in which a child was not substantiated for maltreatment by age 5 years was correctly identified. The area under the ROC curve quantified how well the predictive risk model accurately distinguished spells of maltreated children from spells of children who were not maltreated. The model was developed using Stata, version 12.

Results

Sample Characteristics

An estimated 11,878 children were born in New Zealand between January 1, 2003, and June 1, 2006, who had at least one substantiated report of maltreatment by age 5 years. Among these maltreated children, 83% (n=9816) had a benefit spell that started prior to age 2 years. Therefore, the predictive risk model has the potential to generate risk scores for more than eight of every ten substantiated maltreatment victims before substantiation.

The full sample used in the current study captured information on 57,986 children involved in 103,397 benefit spells (Table 1). Approximately 56.8% of these children were observed during a single benefit spell, 21.9% during two spells, and the remaining 21.3% during three or more spells. Among children in the full sample, 13.3% were substantiated for maltreatment subsequent to

Table 1. Descriptive statistics for the full sample of spells available for predictive risk modeling

Data categories	n
Benefit spells by age 2 years	103,397
Unique children	57,986
Outcome variables	**Proportion[a]**
Any maltreatment	0.150
Neglect	0.064
Emotional abuse	0.106
Physical or sexual abuse	0.019
EXAMPLES OF PREDICTOR VARIABLES	**M (range)**
Primary caregiver characteristics	
Age at birth of child (years)	26.937 (15–75)
Number of older children	0.908 (0–10)
Proportion of time on unemployment benefit during prior 2 years	0.148 (0–1)
Prior court-issued CPS reports for other children	0.007 (0–5)
Prior substantiations for behavioral problems for other children	0.008 (0–5)
Substantiated physical or sexual abuse before age 16 years	0.102 (0–10)
Partner characteristics	
Partner of primary caregiver present	0.289 (0–1)
Partner has criminal record	0.037 (0–1)
Proportion of partner time on sickness benefit during prior 2 years	0.027 (0–1)
Prior neglect substantiations for partner's other children	0.018 (0–5)
Prior police family violence reports for partner's other children	0.019 (0–5)
Youth justice referrals for partner before age 16 years	0.059 (0–30)
Child characteristics	
Number of different caregivers for child	1.366 (1–5)
Court-issued CPS reports for child	0.024 (0–15)
Family group conferences involving child	0.011 (0–5)
Prior substantiated reports of neglect of child	0.008 (0–5)
Prior substantiated reports of emotional abuse of child	0.010 (0–5)
Prior substantiated reports of physical/sexual abuse of child	0.002 (0–5)

Note: Calculations are based on merged administrative data provided by the New Zealand Ministry of Social Development. Predictor variables included here are examples of 242 covariates available in the data set. To protect confidentiality of individuals, all maximum values for nonbinary variables were rounded to the nearest interval of 5.
[a]Proportion of spells with substantiated reports by age 5 years
CPS, child protective services

the start of the benefit spell and before age 5 years. Thus, the predictive risk model was developed to predict an event that occurred among approximately one of every eight risk-scored children.

Validation of the Predictive Risk Model

The final predictive risk model had an area under the ROC curve of 76% (95% CI=75.7, 77.1; Appendix A, available online at www.ajpmonline.org). A model with 100% area under the ROC curve is said to have perfect prognostic strength; a model with 50% is no better than tossing a coin to predict whether a child will be maltreated. The area under the ROC curve provides a summary statistic of model validity, yet a practical means of assessing a model is to consider the proportion of spells in which substantiated maltreatment can be correctly identified. Figure 1 reflects the percentage of children in the full sample with a substantiated maltreatment report based on the risk decile of their first public benefit spell. The 10% of spells with the highest risk scores involved children who had a 47.8% probability of substantiated maltreatment by age 5 years, compared to a 1.7% probability for the 10% of spells falling in the lowest-risk decile.

Table 2 presents an alternative assessment of the predictive power of the model by considering the sensitivity of the risk scores at various cutoff points for the full sample of children. If the threshold for deeming a spell to be high risk included Deciles 9 and 10, this model would result in 20% of children in the highest-risk spells being targeted for some follow-up assessment or intervention. Based on this model, these spells would have included 15.9% of children in the benefit system, less than the expected 20% of children because children at high risk tended to have more than one benefit spell before age 2 years. Yet, the spells in Deciles 9 and 10 would capture 44.0% of children substantiated for maltreatment (and an estimated 37% of all children in this birth cohort substantiated by age 5 years). If the riskiest 10% of spells were targeted (i.e., Decile 10), the model would have identified 24.7% of children receiving benefits and substantiated for maltreatment (and approximately 21% of all children in New Zealand who were substantiated by age 5 years), from just 6.9% of children receiving public benefits.

Discussion

This analysis examined whether administrative data harvested from New Zealand's public benefit and CPS systems were sufficient to predict substantiated maltreatment. Model findings suggest that it is possible to stratify children on the basis of maltreatment risk, with children in the highest-risk decile being 25 times more likely to be substantiated for maltreatment than those in the lowest-risk decile. Among children in the highest-risk decile, 47.2% were substantiated for maltreatment by age 5 years. Findings also indicate that public benefit data captured a significant proportion (i.e., 83%) of New Zealand children substantiated for maltreatment by age 5 years.

The accuracy of this model is similar to digital or film mammography as a method for predicting breast cancer among women without symptoms.[14] In New Zealand, the national prevalence rate of substantiated maltreatment for children aged <5 years is more than 20 times the risk of breast cancer in women offered screening between the ages of 50 and 60 years.[15] Yet, although it is government policy to universally screen these women to increase early identification, no attempt is made to apply the same logic by screening children for maltreatment

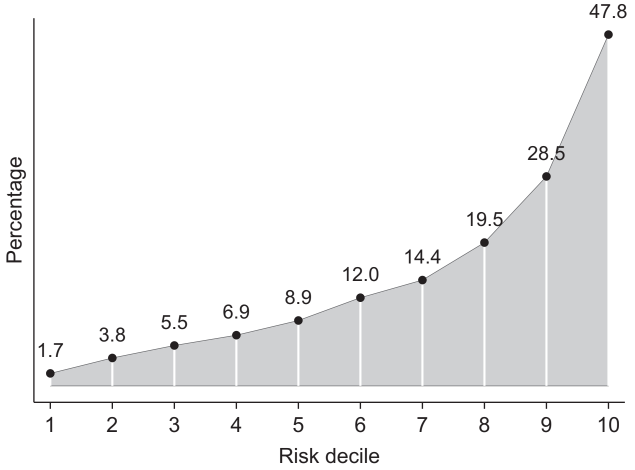

Figure 1. Percentage of children substantiated for maltreatment by age 5 years, stratified by risk decile at first public benefit spell

Table 2. Cumulative percentage of children who received benefits and were substantiated for maltreatment by age 5 years

Risk decile	Percentage of maltreated children identified	Percentage of all children on benefits by age 2 years
1	100.0	100.0
2	98.5	88.4
3	95.1	76.4
4	90.7	65.8
5	85.6	56.0
6	79.3	46.5
7	70.3	36.5
8	59.0	26.1
9	44.0	15.9
10	24.7	6.9

risk. This analysis suggests that an automated predictive risk model using integrated data could be used to identify young children at high risk of maltreatment.

The value of clinical versus statistical prediction has been long debated in the delivery of human services,[16] including child protection.[17,18] In the case of child protection decision making, there is clear evidence that actuarial approaches are superior to clinical attempts to balance the complex and often interacting factors that influence a child's risk.[18,19] Yet, actuarial approaches as presently implemented require expensive and time-consuming clinical training to ensure tool fidelity,[19] and they are infrequently validated on the populations being risk-scored. Additionally, actuarial models have focused on accurately assessing the recurrence of maltreatment rather than predicting a first occurrence, even though a growing body of literature highlights the importance of primary prevention.[10,20–22]

Although a statistical model cannot replace more-comprehensive clinical assessments of a child's risk, automated predictive risk models could be cost-effectively implemented within a broader array of assessment tools employed at varying points in the trajectory of children's engagement with service sectors. The application of an automated predictive risk model has the potential to not only support an upstream shift toward maltreatment prevention activities but also to do so in a cost-effective and targeted manner. Research indicates that early intervention programs often yield greater benefits when offered to mothers and families at higher risk compared to those at low risk.[23] Risk stratification has the potential to maximize the impact of programs that may vary in effectiveness across populations.[11]

To develop the final model, 224 variables were tested, and 132 were selected for inclusion. Variables were maintained in the final model because they provided the strongest means of discriminating between benefit spells with a high risk that a child would be substantiated for maltreatment from those with a low maltreatment risk. Using race/ethnicity as a predictor variable was deemed potentially problematic because of concerns surrounding racial stereotypes or a race-based allocation of interventions. Race/ethnicity, however, had very little influence on the performance of the model (data not shown), consistent with other recent maltreatment research finding that when socioeconomic variables are incorporated, race effects diminish or disappear.[24,25]

The usefulness of an automated predictive risk model depends on not only the predictive strength of the model but also the cost of the prevention services that can be offered to children in high-risk strata. If an intervention is inexpensive, it may be cost effective to provide the service to all children, independent of risk strata. For more costly services of greater intensity, however, there will likely be budgetary threshold for services, and a predictive risk model allows this threshold to be based on a child's risk.

For example, the Nurse Family Partnership (NFP) is a public health program that has been shown to reduce maltreatment risk by 46% (the rate of substantiated maltreatment in the intervention group was 29% compared to 54% in the control group).[26] Combining this effectiveness data with the estimated cost of the NFP evaluation of £6000 ($9500) per family in the United Kingdom in 2010,[27] findings indicate that intervening with the riskiest decile would yield a cost-effectiveness ratio of £26,000 ($41,000) per avoided maltreatment. If all children receiving public benefits were offered NFP, the cost effectiveness would be reduced to £99,000 ($157,000) per avoided maltreatment.

Limitations

A key feature of this predictive risk model is its utilization of administrative data. Although these data were collected for other purposes—such as establishing service eligibility and case planning—this analysis demonstrates the potential for an automated model to harvest extant databases to risk-stratify children at minimal cost. Of course, only a fraction of all maltreated children are substantiated as victims by CPS,[28–30] and not all children substantiated for maltreatment had a public benefit spell by age 2 years. A limitation of this PRM is its inability to risk-score the broader population of children who also might have benefited from early intervention services. Yet, among children captured in benefit data, it is possible to stratify by risk in a manner that could strategically inform the allocation of service interventions.

A second limitation centers on the ethics of using a predictive risk model to assess maltreatment risk. Although such models are frequently used to risk-stratify patients in healthcare settings,[12,31] the application of this approach to child protection presents unique ethical issues. First, predicting risk of maltreatment from data collected for assessing benefit entitlements raises concerns. Unlike healthcare settings, in which these models are used to predict hospital admissions and health outcomes, calculating maltreatment risk scores for children has the potential to stigmatize clients.

Additionally, ethical issues surround the extent to which a prevention agency may have an obligation to intervene once a risk score is computed. For example, if a high-risk family refuses voluntary services, does the agency have any additional obligation to the child? Should it increase its surveillance of the family? In this case, the risk score would preempt maltreatment substantiation (rather than simply risk-stratifying the population). If a caregiver's risk increases because of the history of a new partner, would the agency have an obligation to inform the caregiver of this increased risk?

Although these complex ethical issues must be addressed, reliance on an automated predictive risk model also can enhance decision-making equity. Clinicians who are unable to properly weight relevant factors are forced to rely on heuristic strategies that may be poor predictors of the outcome of interest, as well as biased.[32,33] The use of a computerized model for assigning risk and establishing a common threshold for initial action would reduce clinical preconceptions in maltreatment risk assessments.

Conclusion

The ability to determine a child's risk of substantiated maltreatment at or shortly after birth provides a tremendous opportunity for public health agencies to voluntarily work with families before any coercive CPS involvement is required. PRM offers a cost-effective way of stratifying patients in healthcare settings; this analysis suggests that it also may be usefully applied to vulnerable children, enabling scarce prevention resources to be offered to those at high risk of maltreatment. Future work should explore methodologic improvements in the precision of this PRM through models that allow for the possible non-independence of the multiple benefit spells observed for a child (e.g., random effects probit model) and the development of separate risk models for each type of maltreatment (i.e., neglect, sexual abuse, physical abuse, or emotional abuse). Although ethical questions must be addressed before such a model can be operationalized and implemented, findings from this preliminary analysis in New Zealand suggest the potential application of automated predictive risk modeling as part of a broader, prevention-focused child-protection reform effort.

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Appendix

Supplementary data

Supplementary data associated with this article can be found, in the online version at http://dx.doi.org/10.1016/j.amepre.2013.04.022.