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Suicide and Life-Threatening BEHAVIOR

ORIGINAL ARTICLE

Using electronic health record data to predict future self-harm or suicidal ideation in young people treated by child and youth mental health services

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Abstract

Introduction: Identifying young people who are at risk of self-harm or suicidal ideation (SHoSI) is a priority for mental health clinicians. We explore the utility of routinely collected data in developing a tool to aid early identification of those at risk.

Method: We used electronic health records of 4610 young people aged 5–19 years who were treated by Child and Youth Mental Health Services (CYMHS) in greater Brisbane, Australia. Two Lasso models were trained to predict the risk of future SHoSI in young people currently rated SHoSI; and those who were not.

Results: For currently non-SHoSI children, an Area Under the Receiver Operating Characteristics (AUC) of 0.78 was achieved. Those with the highest risk were 4.97 (CI 4.35–5.66) times more likely to be categorized as SHoSI in the future. For current SHoSI children, the AUC was 0.62.

Conclusion: A prediction model with fair overall predictive power for currently non-SHoSI children was generated. Predicting persistence for SHoSI was more difficult. The electronic health records alone were not sufficient to discriminate at acceptable levels and may require adding unstructured data such as clinical notes. To optimally predict SHoSI models need to be tested and validated separately for those young people with varying degrees of risk.

KEYWORDS

child and youth mental health service, electronic health record data, predictive risk modeling, self-harm or suicidal ideation

INTRODUCTION

In high income countries, suicide is the leading cause of death in adolescents aged 15–29 years and the third leading cause of death in children aged 5–14 years (World Health Organization, 2015). Hence, improving treatment for prevention of suicide is a major focus for research. Studies have shown that there are multiple

risk factors for suicide, for example, suicidal ideation or prior attempts, family history (which is 30%–50% related to heritability) (Lutz et al., 2017), adverse life events, and psychopathology–in particular, affective disorders, disruptive/conduct disorders, and substance use disorders (for an overview of risk factors Wasserman et al. (2021), and Hawton et al. (2012). However, these are very general risk factors and the majority of children and young people exposed to these risk factors will not commit suicide, even if all risk factors are present. This means that they are of little use to clinicians who would like to identify children and young people at high risk of suicide, and to target interventions aimed at suicide prevention.

Machine learning methods are being used more and more as tools to improve prediction, as they allow for more complex models than other statistical methods. However, machine learning models are hampered by the fact that suicide is still, fortunately, a rare event. Therefore, many researchers focus not on suicide as such but on endpoints with higher prevalence rates, for example, self-harm or suicidal ideation (SHoSI) with or without suicidal intent. While on their own, SHoSI has a huge impact on the individual, families and society as a whole, they are also major risk factors for suicide death (Wasserman et al., 2021). Nock et al. (2013), for example, reported that for youth with suicide ideation one-third go on to develop a prevention plan and approximately 50% of that group will attempt suicide.

Despite the large impact of SHoSI and suicide in this young age group, studies using machine learning methods to build prediction models have so far focused primarily or exclusively on adults, and studies including children below 12 years are rare (Bernert et al., 2020; Burke et al., 2019). Two studies using a community sample of adolescents (Hill et al., 2020; Miché et al., 2020), two studies analyzing adolescents attending a hospital (Su et al., 2020; Walsh et al., 2018), and one study focusing on adolescents that presented to a mental health service (Iorfino et al., 2020) showed reasonable prediction of SHoSI. With AUC ranging from 0.74 to 0.97, the studies indicate that these methods can lead to practically useful results. Unsurprisingly previous SHoSI, if included as a predictor, was most strongly related to future self-harm or suicide attempts (Hill et al., 2020;Iorfino et al., 2020; Miché et al., 2020). Moreover, prediction models appeared to perform better when the comparison group was less severe, that is, general hospital patients instead of only children with other self-harm events but no intention for suicide (Walsh et al., 2018), or the general population instead of another clinical group (Iorfino et al., 2020; Miché et al., 2020).

Studies analyzing population-based or hospital-based samples that include many very low risk children can be useful as they can aid in identifying the small group of children in those populations that could benefit from support. In child and youth mental health services, the rate of children who will start or continue to self-harm or express suicidal ideation is far larger. Well optimized prediction models could help mental health services clinicians to provide the right level of treatment to the children and young people at highest risk. However, as became clear from the studies discussed above (Iorfino et al., 2020; Miché et al., 2020; Walsh et al., 2018), prediction is particularly difficult in clinical populations. Iorfino et al. (2020) analyzed a population of children and young people seen in child and youth mental health services and the AUCs for predicting SHoSI were approximately 0.75.

In the current study, we also analyze a clinical population but focus on a group with severe and complex mental health problems and include younger children and children that attend day programmes or inpatient units. Moreover, as the strongest predictor for self-harm is a history of self-harm, we split the sample into two groups: one with no current SHoSI and one with current SHoSI, and built two prediction models. Clinicians are fully aware of the increased risk when a child currently reports SHoSI, therefore a risk model conditional on the child's current status will be the most valuable decision support tool in the clinic.

METHODS

Participants

We obtained data for children aged 5–19 years who presented to child and youth mental health services (CYMHS), at Children's Health Queensland Hospital and Health Service (CHQHHS) in the larger Brisbane area, Australia. CYMHS is a public, that is, free, service providing treatment for children with complex and severe mental health problems. The service includes inpatient units, and outpatient services that is, day programmes and community CYMHS. Treatment is provided by multidisciplinary teams, consisting of child and adolescent psychiatrists, psychologists, social workers, occupational therapists, and speech pathologists, and includes pharmacological and non-pharmacological interventions such as psychotherapy and parental guidance.

The initial patient population consisted of 7137 children who had a routine outcome measure (ROM) observed between 2010 and the end of 2017. For this study, we restricted the population by excluding the following children:

1. Those who started their treatment prior to the study period;
2. Those who did not have two measures of SHoSI; and
3. Those who had multiple SHoSI measures on the same day.

After applying these exclusion criteria, the final study population consisted of 4610 children.

Measures

Information was extracted from electronic health records and included demographics, service use and diagnostic information, in addition to clinician and parent-rated ROMs. ROM were assessed following the National Outcomes and Casemix Collection (NOCC) (Australian Mental Health Outcomes and Classification Network (AMHOCN), 2009) with regular scoring of Health of the Nation Outcome Scales Child and Adolescent Mental Health (HoNOSCA), Children's Global Assessment Scale (CGAS) and a parental Strengths and Difficulties Questionnaire (SDQ).

The outcome measure: Self-harm or suicidal ideation (SHoSI)

The endpoint of interest for this study is SHoSI as measured by item 3 of the HoNOSCA: Non-accidental self-injury. Non-accidental self-injury includes self-harm such as hitting self and self-cutting, suicide attempts, overdoses, hanging, drowning, etc (not including scratching, picking as a direct result of physical illness, accidental self-injury due, for example, to severe learning or physical disability, or illness or injury as a direct consequence of drug or alcohol use.) The HoNOSCA is completed by the clinician using a 5-point scale (from 0 to 4) that ranges from "No problems of this kind during the period rated" (with a score of 0) to "Serious suicidal attempt (e.g., serious overdose), or serious deliberate self-injury" (with a score of 4). A score ≥ 3 is defined as clinically significant.

Predictors

Predictive features included in the model were restricted to information available in the electronic medical health records and included demographics, diagnoses, current and previous HoNOSCA, CGAS, and SDQ measures. Appendix A lists the 93 predictors used for modeling.

Demographic information

Demographic information included gender, age at start of each episode, indigenous status, country of birth, preferred language, and residing suburb. Indigenous status is defined as identifying as Aboriginal and/or Torres Strait Islander, who are the First Nations people of Australia. Suburb postal codes were cross matched against the 2016 Australian Socio-Economic Indexes for Areas from the Australian Bureau of Statistics.[1] This ranks areas in Australia according to relative socio-economic advantage and disadvantage and indicates suburb performance in comparison to the rest of the nation.

Diagnoses and service use

Primary and secondary diagnoses were collected at every case review by the multidisciplinary CYMHS teams, which included senior clinicians, and classified according to the International Statistical Classification of Diseases, 10th revision (ICD-10) (World Health Organization, 2015) classifications for Mental, Behavioral and Neurodevelopmental Disorders (codes F00-99), and the factors influencing health status and contact with health services (codes Z00-99). Diagnoses were also based on the information obtained from the parent/s and child in unstructured diagnostic interviews, sometimes combined with extra collateral information, for example, from a teacher. All diagnoses were included for this study and similar diagnoses were combined into major groups. Appendix B lists the diagnoses groups used for prediction.

Routine outcome measures (ROM)

The HoNOSCA is a 15-item clinician-rated measurement designed to assess child and adolescent outcomes in mental health services including four subscales: behavioral (BEH), symptomatic (SYP), social (SOC), and impairment (IMP), and a total score based on questions 1–13 (Gowers et al., 1999). Questions 14 and 15 were excluded because these pertained to parental knowledge about the child's difficulties and services available to them. HoNOSCA item-03 score, the subscales and the total scores were included in the model.

The CGAS is a clinician-rated measure and provides a global level of adjustment and functioning of clients'

[1] https://www.abs.gov.au/ausstats/abs@.nsf/mf/2033.0.55.001

abilities to carry out different activities in different settings, such as at home, school, or with peers, on a scale of 1–100, focusing on the lowest level of functioning in the past month (Shaffer et al., 1983).

Clinician-rated ROM (CGAS and HoNOSCA) were completed by the health care professional responsible for the child, including child and adolescent psychiatrists, psychologists, social workers, or occupational therapists. All clinicians were offered training to rate these measures. Training completion rates are not available which means questionnaires may have been completed by untrained clinicians. For both instruments, inter-rater reliability has been reported to be good (Pirkis et al., 2005).

This study included all scales of the 25-item parent-rated SDQ that includes five subscales: emotional (EPS), conduct (CPS), hyperactivity (HAS), peer relationship (PPS), and prosocial behaviors (PSS) over the past 6 months (Goodman et al., 2000) and a total difficulties score (TDS) which is the sum of all subscales except the prosocial subscale.

If, according to the NOCC criteria, there were too many items missing for a (sub)scale, this score was coded as missing (AMHOCN, 2009). For children with valid but incomplete ROM, Multiple Imputations in SPSS software were used to generate missing values by maintaining the variance and covariances of individual/global scores (Schlomer et al., 2010).

Ethical approval for use of the data in a de-identified format was obtained from the Human Research Ethics Committee of Children's Health Queensland (HREC/17/QRCH/321). It was further approved by the Health Innovation, Investment and Research Office (HIIRO), Queensland Health, in accordance with the Australia Public Health Act 2005.

Data analysis

The prediction model aims to predict SHoSI following an earlier measure of SHoSI (the "triggering time point" for the prediction). Hence, the data were formatted so that each row represents a point in time when a HoNOSCA is completed. The outcome that is being predicted is whether SHoSI is observed the next time the child has a HoNOSCA. Figure 1 illustrates how data are re-formatted for the prediction task with the concept of a "triggering" HoNOSCA.

Predictors included total and subscale scores for the HoNOSCA, SDQ and CGAS, as measured at the triggering timepoint and previous timepoints (if any), and maximum score across all previous timepoints (if any). We also included as predictors: the total number of previous HoNOSCA, SDQ and CGAS measures, the number of SHoSI ratings, and a variable to indicate whether or not the child ever had a score in the clinical range for SHoSI.

We set out to test the prediction models for two groups separately: (i) *New SHoSI model*: to predict SHoSI conditional on being currently non-SHoSI at the triggering

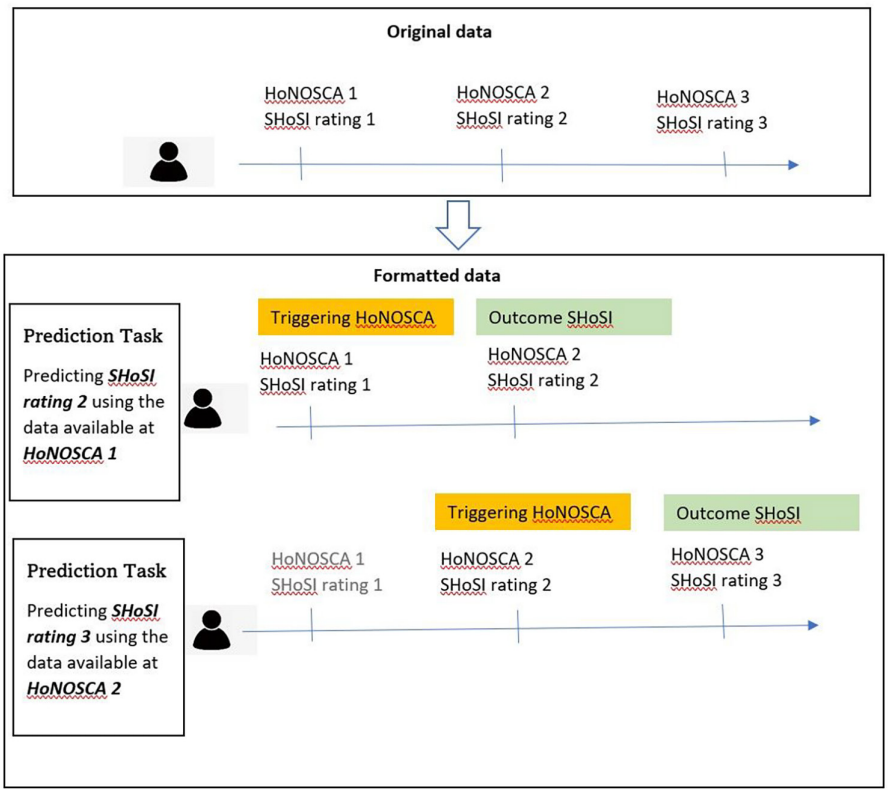

FIGURE 1 An illustration of the prediction task.

HoNOSCA; and (ii) *Persistence SHoSI Model*: to predict future SHoSI conditional on being currently SHoSI (i.e., at the triggering HoNOSCA).

Of the prediction dataset of 15,964 SHoSI ratings, 12,169 were currently non-SHoSI and 3795 were currently SHoSI. The two prediction datasets were randomly split into a training dataset which contained 75% observations and a hold-out test dataset which contained 25% observations. The model was trained using the train set, and all performance metrics were calculated using the test set. We explored LASSO (least absolute shrinkage and selection operator) regularized logistic regression (Tibshirani, 1996). Alternative approaches using Random Forest modeling (Ho, 1995) were also tried, but there were minimal differences found in terms of accuracy.

Figure 2 illustrates the way in which the data sets are constructed.

The LASSO method models the likelihood of a particular categorical outcome as a function of a set of input features. Lasso regularized logistic regression ensures certain weights for input features are set to zero while minimizing prediction error. This method performs feature selection and regularization which results in a more accurate and interpretable model.

We used tenfold cross-validation on the training data to choose the model parameters while dealing with overfitting. All the HoNOSCA measures of a particular child were either assigned to the training set or test set to make the test data set independent from the train data set. Moreover, all the HoNOSCA measures of a child were assigned to a same-cross-validation fold to avoid information leaking across the folds. The predictive model generated the risk probability of SHoSI at the following timepoint.

Model performance was measured using the Area Under the Receiver Operating Characteristics (AUC), Sensitivity (True Positive Rate), Specificity (True Negative Rate) and Positive Predictive Value (PPV). An AUC closer to 1 represents a perfect model. Sensitivity, Specificity and PPV measurements were obtained by splitting up the probabilistic predictions at a cut-off threshold of 0.5.

Models were built using R version 3.6.2 using glmnet (Friedman et al., 2010) package.

RESULTS

The study population consisted of 4610 children and young people and 15,964 triggering HoNOSCAs. The average age of this population at the start of first episode was 13 years, 56% were female and 7% were indigenous. Of the children and young people with more than one HoNOSCA included in the analyses, on average four HoNOSCAs were available with 25% of the children having five or more HoNOSCAs. The average length of time between the "triggering HoNOSCA" and the outcome SHoSI is approximately 105 days with a standard deviation of 147 days. Around 3.6% had a length of time greater than 1 year. Because a number of children had multiple HoNOSCAs, the prediction dataset included 15,964 observations.

The average number of diagnoses of mental and behavioral disorders (i.e., F-code diagnoses) and environmental stressors (i.e., Z-code diagnoses) was three and five respectively. There were 3740 children who only attended a community CYMHS, and 486 children who were only admitted to a day programme or an inpatient unit. There were 384 children who received treatment from both types of services.

Exploratory analysis

To understand the stability of SHoSI through multiple HoNOSCAs, we followed each child from the first HoNOSCA (typically undertaken at the first presentation to a CYMHS) to subsequent ones.

Table 1 presents the dynamics of SHoSI across all HoNOSCAs. At the first HoNOSCA 1470 of the 4610

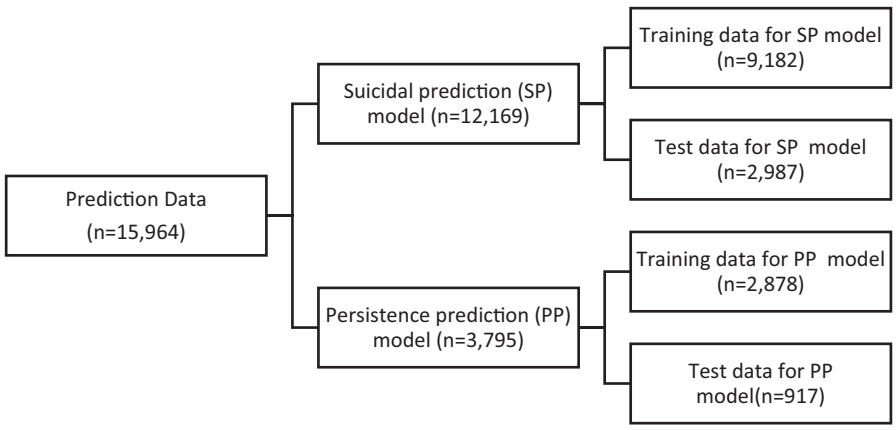

FIGURE 2 Illustration of constructing the data sets for predictions.

Group	Number (%) of children in the prediction sample
Persistently positive SHoSI score	323 (7.01)
Persistently rated as non-SHoSI	2639 (57.24)
Non-SHoSI in first HoNOSCA, but SHoSI in at least one subsequent HoNOSCA	501 (10.87)
SHoSI in first HoNOSCA, but non-SHoSI in all subsequent HoNOSCAs	644 (13.97)
SHoSI in first HoNOSCA, and varies between SHoSI and non-SHoSI in subsequent HoNOSCAs	503 (10.91)

TABLE 1 Dynamics of SHoSI across all HoNOSCAs.

children (31.89%) scored positive, that is, in the clinical range for SHoSI. Of those, 323 scored positive in all subsequent HoNOSCAs. Of those who scored negative for SHoSI at the first HoNOSCA, 2639 scored negative in all subsequent HoNOSCAs. Of those who changed status: 10.9% changed from non-SHoSI to SHoSI, 14.0% switched from SHoSI to non-SHoSI, and 10.9% varied between SHoSI and non-SHoSI. Those who persistently reported SHoSI or non-SHoSI after the first HoNOSCA had on average three subsequent HoNOSCAs, whereas those who changed status had on average seven subsequent HoNOSCAs.

Prediction model for currently non-SHoSI children: The new SHoSI prediction model

Of children who were non-SHoSI in a triggering HoNOSCA, 8.05% were SHoSI in the next HoNOSCA and 91.95% were not.

We present the demographic characteristics in Table 2. As this is per observation, many children are included more than once which means that the variables are not independent. Hence, we have not performed statistical tests to explore whether these variables were related to the next SHoSI score.

The LASSO model yielded an AUC of 0.78, Sensitivity of 0.71 and Specificity of 0.72.[2] To illustrate the predictive power of the model, we grouped predicted risk probabilities into five risk groups based on (roughly) a doubling of prevalence of SHoSI for each group. The test sample was distributed as follows: 15.5% in Group 1; 38.9% in Group 2; 25.3% in Group 3; 15.3% in Group 4 and 5.0% in Group 5. Figure 3 illustrates the prevalence of SHoSI by group. Those who scored 5 based on the LASSO model had a SHoSI prevalence of 32.0% compared to 1.1% of those who scored 1.

[2]Note. Sensitivity, Specificity are calculated using the probability threshold of 0.5.

Appendix C lists the predictors with non-zero weight of the new SHoSI prediction model.

Prediction model for currently SHoSI children: The persistence SHoSI prediction model

Table 3 provides the demographic information on the sample that started off with a positive SHoSI score. Of these children, 52.7% were rated SHoSI in the next HoNOSCA.

The LASSO model yielded an AUC of 0.62, Sensitivity of 0.47 and Specificity of 0.66. Given the poor predictive power, we only generated three groups based on the probabilities with 16.1% of the sample in Group 1, 80.5% in Group 2 and 3.4% in Group 3. The result was a moderate level of discrimination as shown in Figure 4.

Appendix D lists all the predictors with non-zero weight of the persistent SHoSI prediction model.

DISCUSSION

We aimed to test if routine medical data could be used to develop a decision-support tool that would aid in predicting which children were at highest risk for future SHoSI, which is a high indicator of suicide risk. We focused on children and youth aged 5–19 years with complex and severe mental health issues that attended a public child and youth mental health service in the greater area of Brisbane, Australia. The predictors used data routinely collected in clinical practice that can be easily obtained from personal electronic Health Records. The advantage of using these data is that this requires no additional work or effort on the part of clinicians and could be made available through an automated system, for all children.

Given the dynamics of self-harm and suicidal ideation for children moving in and out of SHoSI, we tested a model predicting SHoSI in children who currently were

TABLE 2 Demographics and clinical characteristics of the non-SHoSI sample.

Demographics/clinical characteristics	Overall	Next SHoSI score = NO	Next SHoSI score = YES
N (#SHoSI ratings)	12,169	11,190	979
Age (mean (SD))	12 (3)	12 (3)	14 (2)
Gender (%)			
Male	49.61	51.28	30.54
Female	50.28	48.62	69.25
Other	0.11	0.10	0.20
Indigenous Status (%)			
Aboriginal but Not Torres Strait Islander Origin	5.95	6.03	5.01
Both Aboriginal and Torres Strait Islander Origin	0.75	0.77	0.51
Neither Aboriginal Nor Torres Strait Islander Origin	92.85	92.73	94.18
Torres Strait Islander but Not Aboriginal Origin	0.42	0.43	0.31
Not Stated/Unknown	0.03	0.04	0.00
Area deprivation percentile (100% means the richest postal code) (Mean (SD))	61 (27)	61 (27)	62 (26)
Country of birth = Australia (%)	90.93	91.01	89.99
Language = English (%)	97.87	97.80	98.67

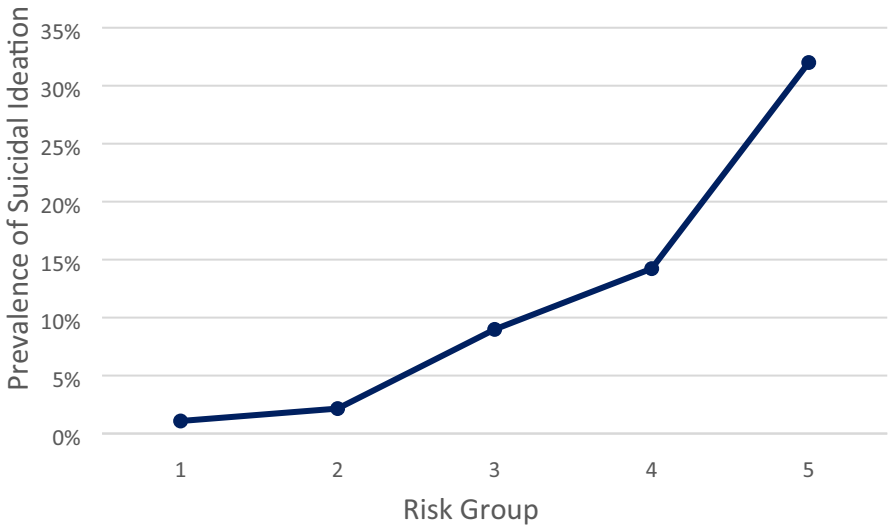

FIGURE 3 Prevalence of SHoSI per Risk Group in the test dataset for those whose triggering HoNOSCA score was non-SHoSI.

reporting non-SHoSI and another model for children who currently were reporting SHoSI. The prediction was more accurate for those currently reporting non-SHoSI (AUC 0.78) than for those currently reporting SHoSI (AUC 0.62). The most predictive variables for both models, in line with earlier findings (Hill et al., 2020; Iorfino et al., 2020; Miché et al., 2020; Su et al., 2020; Walsh et al., 2018), were: the SHoSI score at the triggering timepoint, female gender, and age (with a higher age being related to a higher risk). Therefore, even if a child scored below the clinical threshold for SHoSI, that is, deemed to be non-SHoSI, whether the score was 0, 1 or 2, it did make a difference in the prediction of future SHoSI. Other predictive variables in the non-SHoSI model, in line with previous literature, were: mood disorders and post-traumatic stress symptoms as well as higher scores on the ROMs. Other anxiety disorders and ADHD were related to a lower risk for SHoSI in the non-SHoSI group.

Demographics/clinical characteristics	Overall	SHoSI in the next HoNOSCA = NO	SHoSI in the next HoNOSCA = YES
N (#SHoSI ratings)	3795	1797	1998
Age (mean (SD))	14(2)	14(2)	15(2)
Gender (%)			
Male	26.06	31.39	21.27
Female	73.89	68.50	78.73
Other	0.05	0.11	0.00
Indigenous Status (%)			
Aboriginal but Not Torres Strait Islander origin	5.22	5.56	4.90
Both Aboriginal and Torres Strait Islander origin	0.39	0.22	0.55
Neither Aboriginal Nor Torres Strait Islander origin	94.20	93.82	94.39
Torres Strait Islander but Not Aboriginal origin	0.26	0.39	0.15
Not Stated/Unknown	0.00	0.00	0.00
Area deprivation percentile (100% means the richest postal code) (Mean (SD))	62(27)	62(27)	62(26)
Country of birth = Australia (%)	89.67	88.48	90.74
Language = English (%)	98.97	98.94	99.90

TABLE 3 Demographics and clinical characteristics of currently suicidal (SHoSI) sample.

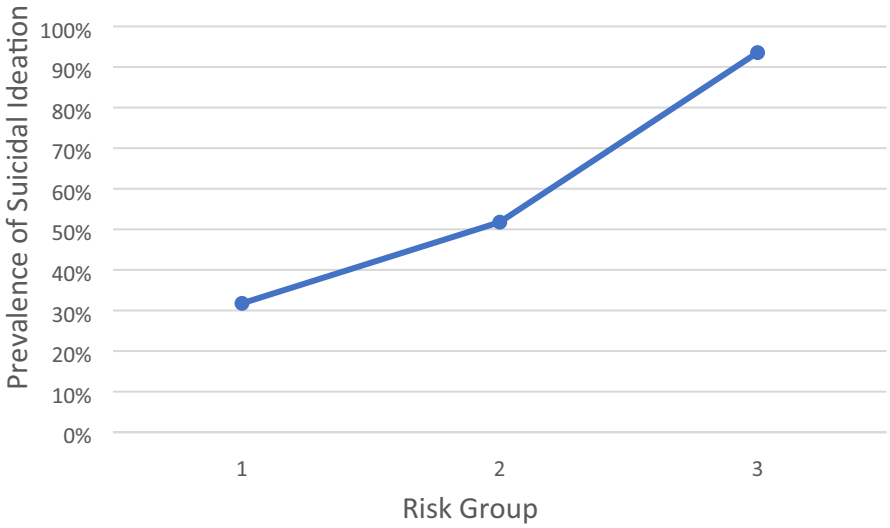

FIGURE 4 Prevalence of SHoSI per Risk Group in the test dataset for those whose triggering HoNOSCA was SHoSI.

A difference between the two models was that an adjustment disorder diagnosis was associated with a higher suicide risk in non-SHoSI children while it was related to a lower risk in SHoSI children. The diagnosis of adjustment disorder is made when mental health symptoms are considered to be a consequence of stressful circumstances and not explained by other diagnoses. Post-traumatic stress symptoms seem to be in line with a higher risk in non-SHoSI children while also increasing the risk for SHoSI children. In the group of current SHoSI children, where none of the other diagnoses are predictive, it could be that a diagnosis of adjustment disorder is protective,

as it means that there is no other more severe disorder present.

Comparing the predictive ability of our two models to previous studies (Hill et al., 2020; Iorfino et al., 2020; Miché et al., 2020; Su et al., 2020; Walsh et al., 2018), shows that the AUC in our current SHoSI model was smaller. The AUC for the non-SHoSI model, on the other hand, was similar to the AUC found in a study analyzing a comparable population (Iorfino et al., 2020) and only slightly lower than in a study analyzing a community sample (Miché et al., 2020).

The fact that the most predictive variables for both models were age, gender and the SHoSI measure at the triggering timepoint raises the question of 'what is gained from a prediction model built with many input variables derived from electronic health records, over a simple prediction model based on only a child's age, gender and the SHoSI measure at the triggering timepoint?' To answer this question, we built a simple prediction model (i.e., lasso model) based on the three input variables and generated the risk groups. The AUC for the non-SHoSI group was 0.74 for the simple prediction model, that is, 0.04 lower than the model including all variables. The AUC for the current SHoSI group was 0.60 for the simple prediction model, that is, 0.02 lower than the model including all variables. Table 4 shows the prevalence rates in different risk groups for the two prediction analyses.

For current non-SHoSI children, compared to the simple model, the prediction model with all input variables assigned 30.67% more children with SHoSI to the highest risk group (5), whereas it included 27.78% less children to the lowest risk group (1). None of these differences were statistically significant. For current SHoSI children, compared to the simple model, the prediction model based on all input variables assigned 53.86% more children with SHoSI to the highest risk group (3) which is statistically significant. It included 16.44% less children with SHoSI to the lowest risk group (1).

These results indicate that the ROMs and diagnostic variables only slightly improve the prediction above the already known risk factors. Previous studies compared the performance of regression models to machine learning models including all variables. Only Walsh et al. (2018) found a difference of >0.2 between logistic regression models and Random Forest models, with both methods using the same predictors. In Su et al. (2020), Miché et al. (2020) and Iorfino et al. (2020) the differences between machine learning models and logistic regression models were far smaller. Nevertheless, the small improvement in prediction that was found using all variables in the machine learning models, could indicate that extending the models with unstructured data will lead to further improvement. A recent review of machine learning in suicide research (Kirtley et al., 2022) suggested applying natural language processing of clinical notes to improve prediction models as this will better incorporate data on psychosocial risk and protective factors that are neglected when only using structured data. Another option would be to draw in a larger range of data from non-health systems such as child protection, schooling, and education. The results from analyses including the latter information would indicate which of these variables were most important to include in a clinical decision support tool and should therefore become part of the structured electronic health record data.

LIMITATIONS AND FUTURE DIRECTIONS

A limitation of this study is that it was restricted to data that were easily obtained from the electronic health

TABLE 4 SHoSI prevalence comparison for prediction models based on all input variables against the simple prediction model based on only age, gender and the SHoSI measure at the triggering timepoint (for the test dataset).

Risk group	Prediction model based on all input variables prevalence % (95% CI)	Prediction model based on age, gender and SHoSI measure prevalence % (95% CI)
For Current Non-SHoSI children		
1	1.08 [0.13, 2.03]	1.38 [0.61, 2.17]
2	2.15 [1.32, 2.99]	3.32 [1.81, 4.83]
3	8.98 [6.94, 11.02]	4.59 [2.39, 6.81]
4	14.22 [11.01, 17.44]	11.89 [9.96, 13.82]
5	32.00 [24.45, 39.55]	24.49 [17.46, 31.52]
For Current SHoSI children		
1	31.76 [24.17, 39.34]	36.98 [30.09, 43.87]
2	51.76 [48.15, 55.37]	45.22 [39.93, 50.50]
3	93.55 [84.39, 102.71]	60.80 [55.86, 65.72]

records. Moreover, the sample size for the current SHoSI group was still relatively small. Given that all public child and youth mental health services in Australia use the same ROM and diagnostic classification, the sample size could be increased by combining patient populations across all of Australia. In addition to incorporating text data from clinical notes and other registers, including genetic information could also improve prediction. This would require collecting DNA in the clinic but given the tremendous progress in the field of psychiatric genetics, this may soon prove also clinically useful (Murray et al., 2021). In adults, polygenic risk scores for suicide death and for psychiatric disorders, indicating an individual's genetic vulnerability, were predictive of suicide death (Docherty et al., 2020).

There are undoubtedly limitations in ML models such as the value of a model does not only depend on its accuracy measured entirely based on the electronic health records. It also depends on how accurate clinician's predictions based on clinical judgment alone. If the model is no better than the clinician, there is no use in implementing it (Salganik et al., 2020). However, we cannot truly assess the model's accuracy until it is put into action alongside clinicians. It is through this deployment that we can establish a fair and comprehensive comparison between the model's accuracy and the clinician's own accuracy.

CONCLUSIONS

We showed that we can build prediction models with predictive accuracy using data routinely collected in clinical practice and obtained from electronic health records. Predicting future SHoSI is more accurate in reported non-suicidal children where the prediction was reasonable. Predicting persistence is more difficult, and information from health records alone was not able to sufficiently discriminate the risk of SHoSI. This indicates that predictions of SHoSI need to be modeled separately depending on the child's degree of risk, as the accuracy of the model and the predictors included can vary. For both models, further analyses showed that the prediction in the models which included all variables was only slightly better than the models that included only the known risk factors, indicating that more complex models are necessary to adequately predict self-harm or suicide ideation.

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CONFLICT OF INTEREST STATEMENT

We have no known conflict of interest to disclose.

DATA AVAILABILITY STATEMENT

Data can only be made available if the researcher has approval from Queensland Health, the data custodian.

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APPENDIX A

All the predictors used for modeling

Name	Meaning
PRI_current_HoNOSCA3	HoNOSCA item 3 score at the triggering timepoint
PRI_current_BEH	HoNOSCA "Behavior" subscale score at the triggering timepoint
PRI_current_IMP	HoNOSCA "Impairment" subscale score at the triggering timepoint
PRI_current_SYP	HoNOSCA "Symptom" subscale score at the triggering timepoint
PRI_current_SOC	HoNOSCA "Social" subscale score at the triggering timepoint
PRI_current_HoNOSCA_SUM	The total HoNOSCA (sum of subscales) at the triggering timepoint
PRI_ageatepisstart	Age at the start of the service episode where triggering HoNOSCA rating is done
PRI_score	The socio-economic index according to the postcode which represents the socio-economic advantage, higher score = greater socio-economic advantage
PRI_score_missing	Indicate whether the score is missing
PRI_percentile	The percentile of the postcode score
PRI_diag_ADHDdiag	Indicate whether child is diagnosed/experienced with Hyperkinetic disorders

(Continues)

APPENDIX A (Continued)

Name	Meaning
PRI_diag_AdjustmentDisorder	Indicate whether child is diagnosed with adjustment disorders
PRI_diag_AnxietyOther	Indicate whether child is diagnosed/experienced with other anxiety disorders
PRI_diag_ConductDisorder	Indicate whether child is diagnosed/experienced with conduct disorder
PRI_diag_EatingDisorders	Indicate whether child is diagnosed/experienced with eating disorders
PRI_diag_EmotionSocialF	Indicate whether child is diagnosed with Emotions or social functioning disorders with onset specific to child/adolescence
PRI_diag_FamhistBMDis	Indicate whether child is diagnosed with Family history behavioral and mental disorders
PRI_diag_GAD	Indicate whether child is diagnosed with Generalized Anxiety disorder
PRI_diag_GenderIDDisorder	Indicate whether child is diagnosed with gender identity disorders
PRI_diag_MentalRetardation	Indicate whether child is diagnosed with intellectual disabilities
PRI_diag_MixConductEmotion	Indicate whether child is diagnosed with mixed disorders of conduct and emotions
PRI_diag_MoodDisorder	Indicate whether child is diagnosed with Mood [affective] disorders
PRI_diag_OCD	Indicate whether child is diagnosed with obsessive-compulsive disorder
PRI_diag_OrganicMentalDis	Indicate whether child is diagnosed with organic mental disorders
PRI_diag_OtherDevelopmDis	Indicate whether child is diagnosed with Other specific developmental disorders (speech and language, skolastic skills, motor function, or other)
PRI_diag_OtherPrimSupp	Indicate whether child is diagnosed with Other Problems in Primary Support
PRI_diag_OtherbeEmMental	Indicate whether child is diagnosed with Other behavioral emotional and mental disorders
PRI_diag_PanicDisorder	Indicate whether child is diagnosed with panic disorder
PRI_diag_PersonalityDis	Indicate whether child is diagnosed with Specific or mixed personality disorders
PRI_diag_PervasiveDevDis	Indicate whether child is diagnosed with Pervasive developmental disorders
PRI_diag_PhobicDisorder	Indicate whether child is diagnosed with Phobic anxiety disorders
PRI_diag_ProbEducLit	Indicate whether child is diagnosed with Education & Literacy Problems
PRI_diag_ProbNegLife	Indicate whether child is diagnosed with Negative Life Events
PRI_diag_ProbSocEnv	Indicate whether child is diagnosed with social environment problems
PRI_diag_ProbUpbring	Indicate whether child is diagnosed with problems upbringing
PRI_diag_Psychosis	Indicate whether child is diagnosed with schizophrenia, schizotypal and delusional disorders
PRI_diag_SeparaAnxietyDis	Indicate whether child is diagnosed with Separation anxiety disorder
PRI_diag_SleepDisorders	Indicate whether child is diagnosed with Nonorganic sleep disorders
PRI_diag_SomatoformDissConv	Indicate whether child is diagnosed with Somatoform, dissociative and conversion disorders
PRI_diag_StressRelaDisorder	Indicate whether child is diagnosed with Acute or post-traumatic stress reactions or other
PRI_diag_SubstanceUse	Indicate whether child is diagnosed with Mental and behavioral disorders due to psychoactive substance use
PRI_diag_TicDisorder	Indicate whether child is diagnosed with TIC disorders
PRI_prev_HoNOSCA_count	Number of prior HoNOSCA ratings
PRI_prev_HoNOSCA3	HoNOSCA item 03 score at the previous timepoint
PRI_prev_max_HoNOSCA	Maximum HoNOSCA item 03 score across all previous timepoints
PRI_prev_BEH	HoNOSCA "Behavior" subscale score at the previous timepoint
PRI_prev_max_BEH	Maximum HoNOSCA "Behavior" subscale score across all previous timepoints
PRI_prev_IMP	HoNOSCA "Impairment" subscale score at the previous timepoint.
PRI_prev_max_IMP	Maximum HoNOSCA "Impairment" subscale score across all previous timepoints.
PRI_prev_SYP	HoNOSCA "Symptom" subscale score at the previous timepoint
PRI_prev_max_SYP	Maximum HoNOSCA "Symptom" subscale score across all previous timepoints
PRI_prev_SOC	HoNOSCA "Social" subscale score at the previous timepoint

APPENDIX A (Continued)

Name	Meaning
PRI_prev_max_SOC	Maximum HoNOSCA "Social" subscale score across all previous timepoints
PRI_prev_HoNOSCA_SUM	Total HoNOSCA score at the previous timepoint
PRI_prev_max_HoNOSCA_SUM	Maximum of total HoNOSCA scores across all previous timepoints
PRI_ever_suicidal_before	Indicated whether the child is rated SHoSI ever before
PRI_prev_suicidal_counts	Number of times the child is rated SHoSI ever before
PRI_num_prev_HoNOSCA	Number of times HoNOSCA ratings are done previously
PRI_num_previous_CGAS	Number of times CGAS ratings are done previously
PRI_current_CGAS	CGAS score given at the triggering timepoint
PRI_prev_CGAS	CGAS score at the previous timepoint
PRI_prev_max_CGAS	Maximum CGAS score across all previous timepoints
PRI_no_prev_CGAS	Indicate whether there was no CGAS done prior to triggering timepoint
PRI_no_current_CGAS	Indicate whether there was no CGAS done at the triggering timepoint
PRI_num_prev_SDQ	Number of times SDQ ratings are done previously
PRI_current_ESS	SDQ "Emotional symptoms" subscale score given at the triggering timepoint
PRI_prev_ESS	SDQ "Emotional symptoms" subscale score given at the previous timepoint
PRI_prev_max_ESS	Maximum SDQ "Emotional symptoms" subscale score across all previous timepoints
PRI_current_CPS	SDQ "Conduct problems" subscale score given at the triggering timepoint
PRI_previous_CPS	SDQ "Conduct problems" subscale score given at the previous timepoint
PRI_prev_max_CPS	Maximum SDQ "Conduct problems" subscale score across all previous timepoints
PRI_current_HAS	SDQ "Hyperactivity/inattention" subscale score given at the triggering timepoint
PRI_prev_HAS	SDQ "Hyperactivity/inattention" subscale score at the previous timepoint
PRI_prev_max_HAS	Maximum SDQ "Hyperactivity/inattention" subscale score across all previous timepoints
PRI_current_PPS	SDQ "Peer Relationship problems" subscale score given at the triggering timepoint
PRI_prev_PPS	SDQ "Peer Relationship problems" subscale score at the previous timepoint
PRI_prev_max_PPS	Maximum SDQ "Peer Relationship problems" subscale score across all previous timepoints
PRI_current_PSS	SDQ "Prosocial behavior" subscale score given at the triggering timepoint
PRI_prev_PSS	SDQ "Prosocial behavior" subscale score at the previous timepoint
PRI_prev_max_PSS	Maximum SDQ "Prosocial behavior" subscale score across all previous timepoints
PRI_current_TDS	Total SDQ score at the triggering timepoint
PRI_prev_TDS	Total SDQ score at the previous timepoint
PRI_prev_max_TDS	Maximum of Total SDQ score across all previous timepoints
PRI_no_prev_SDQ	Indicate whether there was no SDQ done prior to triggering timepoint
PRI_no_current_SDQ	Indicate whether there was no SDQ done at the triggering timepoint
PRI_sex_1	Indicate whether child is a Female
PRI_sex_2	Indicate whether child is a Male
PRI_sex_3	Indicate whether child's sex is reported as other
PRI_countryofbirth_AUS	Indicate whether child's country of birth is Australia
PRI_language_EN	Indicate whether child's language is English
PRI_Indigenous_Status	Indicate whether child's Indigenous status is Aboriginal and/or Torres Strait Islander Origin
PRI_Indigenous_Status_Unknown	Indicate whether child's Indigenous status is Unknown

APPENDIX B

Diagnoses groups used for prediction model

Group	Diagnoses codes
Hyperkinetic disorders	"F90","F90.0","F90.1″,"F90.8" ,"F90.9"
Conduct disorder 'Conduct disorders	"F91","F91.0","F91.1","F91.2","F91.3","F91.8","F91.9"
Mixed disorders of conduct and emotions	"F92","F92.0","F92.8","F92.9"
Emotions or social functioning disorders with onset specific to child/adol	"F93.3","F93.8","F93.9","F94","F94.0","F94.1","F94.2","F94.8" ,"F94.9"
Separation anxiety disorder	"F93","F93.0"
Tic disorders	"F95","F95.0","F95.1","F95.2","F95.8","F95.9"
Organic mental disorders	"F02","F02.0","F02.1","F02.2","F02.3","F02.4","F02.8","F03","F04","F05","F05.0","F05.1","F05.8","F05.9","F06","F06.0","F06.1","F06.2","F06.3","F06.4","F06.5","F06.6","F06.7","F06.8","F06.9","F07","F07.0","F07.1","F07.2","F07.8","F07.9","F09"
Mental and behavioral disorders due to psychoactive substance use	"F10","F10.0","F10.1","F10.2","F10.3","F10.4","F10.5","F10.6","F10.7","F10.8","F10.9","F11","F11.0","F11.1","F11.2","F11.3","F11.4","F11.5","F11.6","F11.7" ,"F11.8","F11.9","F12","F12.0","F12.1","F12.2","F12.3","F12.4","F12.5","F12.6","F12.7","F12.8","F12.9","F13","F13.0","F13.1","F13.2","F13.3","F13.4","F13.5","F13.6","F13.7","F13.8","F13.9","F14","F14.0","F14.1","F14.2","F14.3","F14.4","F14.5","F14.6","F14.7","F14.8","F14.9","F15","F15.0","F15.1","F15.2","F15.3","F15.4","F15.5","F15.6","F15.7","F15.8","F15.9","F16","F16.0","F16.1","F16.2","F16.3","F16.4","F16.5","F16.6","F16.7","F16.8","F16.9","F17","F17.0","F17.1","F17.2","F17.3","F17.4","F17.5","F17.6","F17.7","F17.8","F17.9","F18","F18.0","F18.1","F18.2","F18.3","F18.4","F18.5","F18.6","F18.7","F18.8","F18.9","F19","F19.0","F19.1","F19.2","F19.3","F19.4" ,"F19.5","F19.6","F19.7","F19.8","F19.9"
Schizophrenia, schizotypal and delusional disorders	"F20","F20.0","F20.1","F20.2","F20.3","F20.4","F20.5","F20.6","F20.8","F20.9","F21","F22","F22.0","F22.8","F22.9","F23","F23.0","F23.1","F23.2","F23.3","F23.8","F23.9","F24","F25","F25.0","F25.1","F25.2","F25.8","F25.9","F28","F29"
Phobic anxiety disorders	"F40","F40.00","F40.01","F40.0","F40.1","F40.2","F40.21","F40.22","F40.23","F40.24","F40.29","F40.8","F40.9","F93.1","F93.2"
Panic disorder	"F41","F41.0"
Generalized Anxiety disorder	"F41.1"
Other anxiety disorders	"F41.2","F41.3","F41.8","F41.9"
Mood [affective] disorders	"F30","F30.0","F30.1","F30.2","F30.8","F30.9","F31","F31.0","F31.1","F31.2","F31.3","F31.4","F31.5","F31.6","F31.7","F31.8","F31.9","F32","F32.0" ,"F32.1","F32.2","F32.3","F32.8","F32.9","F33","F33.0","F33.1","F33.2","F33.3","F33.4","F33.8","F33.9","F34","F34.0","F34.1","F34.8","F34.9","F38","F38.0","F38.1","F38.8","F39","F32.10","F32.11","F32.20" ,"F32.01"
Obsessive-compulsive disorder	"F42","F42.00","F42.0","F42.1","F42.2","F42.8","F42.9"
Acute or post-traumatic stress reactions or other	"F43.0","F43.1","F43.10","F43.11","F43.12","F43.8","F43.9"
Adjustment disorders	"F43.2","F43.20","F43.21","F43.22","F43.23","F43.24","F43.25" ,"F43.29"
Somatoform, dissociative and conversion disorders	"F44","F44.0","F44.1","F44.2","F44.3","F44.4","F44.5","F44.6","F44.7","F44.8","F44.9","F44.81","F44.89","F45","F45.0","F45.1" ,"F45.2","F45.20","F45.21","F45.22","F45.29","F45.4","F45.41" ,"F45.42","F45.8","F45.9","F44.82","F45.3","F45.31"
Eating disorders	"F50","F50.0","F50.1","F50.2","F50.3","F50.4","F50.5","F50.8" ,"F50.9"
Nonorganic sleep disorders	"F51","F51.0","F51.1","F51.2","F51.3","F51.4","F51.5","F51.8" ,"F51.9"

APPENDIX B (Continued)

Group	Diagnoses codes
Specific or mixed personality disorders	"F60","F60.0","F60.1","F60.2","F60.3","F60.4","F60.5","F60.6","F60.7","F60.8","F60.9","F60.31","F61","F62","F62.0","F62.1","F62.8","F62.9"
Gender Identity disorders	"F64","F64.0","F64.1","F64.2","F64.8","F64.9"
Intellectual disabilities	"F79.0","F70.0","F70.1","F70.8","F70.9","F79.1","F71.0","F71.1","F71.8","F71.9","F79.8","F72.0","F72.1","F72.8","F72.9","F79.9","F73.0","F73.1","F73.8","F73.9","F78","F78.0","F78.1","F78.8","F78.9"
Other specific developmental disorders (speech and language, skolastic skills, motor function, or other)	"F80","F80.0","F80.1","F80.2","F80.3","F80.8","F80.9","F81","F81.0","F81.1","F81.2","F81.3","F81.8","F81.9","F82","F83","F88","F89"
Pervasive developmental disorders F84	"F84","F84.0","F84.1","F84.2","F84.3","F84.4","F84.5","F84.8","F84.9"

Group	Diagnoses codes
Other_behav_emot_mental	"F98","F98.0","F98.1","F98.2","F98.3","F98.4","F98.5","F98.6","F98.7"
Education & Literacy Probs	"Z55","Z55.0","Z55.1","Z55.2","Z55.3","Z55.4","Z55.5","Z55.6","Z55.7","Z55.8","Z55.9"
Social Environ Probs	"Z60","Z60.0","Z60.1","Z60.2","Z60.3","Z60.4","Z60.5","Z60.6","Z60.7","Z60.8","Z60.9"
Other Probs Primary Support	"Z63","Z63.0","Z63.1","Z63.2","Z63.3","Z63.4","Z63.5","Z63.6","Z63.7","Z63.8","Z63.9"
Fam history bev & men dis	"Z81","Z81.0","Z81.1","Z81.2","Z81.3","Z81.8","Z81.4"
Probs Upbringing	"Z62","Z62.0","Z62.1","Z62.2","Z62.3","Z62.4","Z62.5","Z62.6","Z62.7","Z62.8","Z62.9"
Neg Life Events Z61	"Z61","Z61.0","Z61.1","Z61.2","Z61.3","Z61.4","Z61.5","Z61.6","Z61.7","Z61.8","Z61.9"

APPENDIX C

Weighted (with non-zero weight) Predictors of the Prediction Model for currently non-SHoSI children

Name	Meaning	Weight
PRI_current_HoNOSCA_3	HoNOSCA item 3 score at the triggering timepoint	0.72122
PRI_current_BEH	HoNOSCA "Behavior" subscale score at the currenttimepoint	0.036386
PRI_ageatepisstart	Age at the start of the service episode where triggering HoNOSCA is done	0.080578
PRI_percentile	The percentile of the postcode score which represents the socio-economic advantage	0.001981
PRI_diag_ADHDdiag	Indicate whether child is diagnosed/experienced with Hyperkinetic disorders	−0.21519
PRI_diag_AdjustmentDisorder	Indicate whether child is diagnosed with adjustment disorders	0.111583
PRI_diag_EmotionSocialF	Indicate whether child is diagnosed with Emotions or social functioning disorders with onset specific to child/adolescence	−0.00588
PRI_diag_FamhistBMDis	Indicate whether child is diagnosed with Family history behavioral and mental disorders	−0.14098
PRI_diag_GAD	Indicate whether child is diagnosed with Generalized Anxiety disorder	−0.17873
PRI_diag_GenderIDDisorder	Indicate whether child is diagnosed with gender identity disorders	0.249764
PRI_diag_MoodDisorder	Indicate whether child is diagnosed with Mood [affective] disorders	0.099412
PRI_diag_OCD	Indicate whether child is diagnosed with obsessive-compulsive disorder	−0.15253
PRI_diag_OtherDevelopmDis	Indicate whether child is diagnosed with Other specific developmental disorders (speech and language, skolastic skills, motor function, or other)	−0.00287

(Continues)

APPENDIX C (Continued)

Name	Meaning	Weight
PRI_diag_OtherPrimSupp	Indicate whether child is diagnosed with Other Problems in Primary Support	−0.03868
PRI_diag_OtherbeEmMental	Indicate whether child is diagnosed with Other behavioral emotional and mental disorders	−0.21435
PRI_diag_PanicDisorder	Indicate whether child is diagnosed with panic disorder	−0.03845
PRI_diag_PersonalityDis	Indicate whether child is diagnosed with Specific or mixed personality disorders	−0.00309
PRI_diag_PervasiveDevDis	Indicate whether child is diagnosed with Pervasive developmental disorders	0.011325
PRI_diag_PhobicDisorder	Indicate whether child is diagnosed with Phobic anxiety disorders	−0.19138
PRI_diag_ProbEducLit	Indicate whether child is diagnosed with Education & Literacy Problems	−0.05748
PRI_diag_ProbNegLife	Indicate whether child is diagnosed with Negative Life Events	−0.02144
PRI_diag_SeparaAnxietyDis	Indicate whether child is diagnosed with Separation anxiety disorder	−0.11755
PRI_diag_SleepDisorders	Indicate whether child is diagnosed with Nonorganic sleep disorders	−0.03154
PRI_diag_StressRelaDisorder	Indicate whether child is diagnosed with Acute or post-traumatic stress reactions or other	0.140422
PRI_diag_SubstanceUse	Indicate whether child is diagnosed with Mental and behavioral disorders due to psychoactive substance use	0.04198
PRI_diag_TicDisorder	Indicate whether child is diagnosed with TIC disorders	−0.23673
PRI_prev_HoNOSCA3	HoNOSCA item 03 score at the previous timepoint	0.176779
PRI_prev_max_HoNOSCA3	Maximum HoNOSCA item 03 score across all previous timepoints	0.159451
PRI_prev_max_BEH	Maximum HoNOSCA “Behavior” subscale score across all previous timepoints	0.016398
PRI_prev_max_IMP	Maximum HoNOSCA “Impairment” subscale score across all previous timepoints	−0.00575
PRI_prev_max_SOC	Maximum HoNOSCA “Social” subscale score across all previous timepoints	−0.01721
PRI_prev_suicidal_counts	Number of times the child is rated SHoSI ever before	0.127671
PRI_num_prev_CGAS	Number of times CGAS ratings are done previously	−0.00797
PRI_current_CGAS	CGAS score given at the timepoint	−0.00926
PRI_prev_max_CGAS	Maximum CGAS score across all CGAs done in previous timepoints	−0.00092
PRI_current_ESS	SDQ “Emotional symptoms” subscale score given at the triggering timepoint	0.018456
PRI_prev_CPS	SDQ “Conduct problems” subscale score given the previous timepoint	0.016024
PRI_prev_max_PSS	Maximum SDQ “Prosocial behavior” subscale score across all SDQs done in previous timepoints	−0.01268
PRI_sex_1	Indicate whether child is a Female	0.00080
PRI_sex_2	Indicate whether child is a Male[3]	−0.43718

[3] Note that we have a third sex group which is sex = missing. Hence the weighting of both female and male predictors.

APPENDIX D

Weighted (with non-zero weight) Predictors of the Prediction Model for children who currently score positive on SHoSI

Name	Meaning	Weight
PRI_current_HoNOSCA3	HoNOSCA item 3 score at the triggering timepoint	0.302042
PRI_current_SOC	HoNOSCA "Social" subscale score at the triggering timepoint	0.006114
PRI_current_HoNOSCA_SUM	HoNOSCA total score at the triggering timepoint	0.001941
PRI_ageatepisstart	Age at the start of the service episode where triggering HoNOSCA is done	0.022786
PRI_diag_AdjustmentDisorder	Indicate whether child is diagnosed with adjustment disorder	−0.27893
PRI_prev_HoNOSCA3	HoNOSCA item 03 score at the previous timepoint	0.132906
PRI_prev_suicidal_counts	Number of times the child is rated SHoSI ever before	0.052872
PRI_current_PPS	SDQ "Peer Relationship Problems" subscale score given at the triggering timepoint	−0.02981
PRI_sex_1	Indicate whether the child is a Female	0.184989
PRI_countryofbirth_AUS	Indicate whether child's country of birth is Australia	0.002366