Research Bulletin

Research Bulletin No: 38
October 2018

The Community Triage Risk Assessment Scale (Community TRAS)

A statistical model for predicting recidivism among community-based offenders

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Aims

The aim of this study was to develop a statistical tool that employs readily available historical variables to accurately predict the probability of a community-based offender returning to Corrective Services New South Wales (CSNSW) supervision as a result of reconviction within two years. This tool, named the Community Triage Risk Assessment Scale (Community TRAS), is intended to assist decision making about referral to more comprehensive assessment and case management.

Methods

Models were developed on a total sample of 39,153 offenders under community supervision between July 2010 and June 2013. Optimal predictive models were generated by logistic regression modelling and verified using cross validation and bootstrapping analytical methods.

Results

A number of predictors of recidivism were included in the final model including age, duration of supervision, order type, Copas rate, indices of previous offending and time in custody, and Indigenous status. The model was found to have a satisfactory level of discrimination for offenders' reconviction and return to supervision. Model verification techniques indicated stability of the Community TRAS across samples. Hypothetical scenario modelling indicated that population level screening of offenders with the Community TRAS could improve allocation of limited existing assessment resources to individuals who are more likely to reoffend.

Conclusion

Accurate and efficient identification of offenders who are at higher risk of returning to CSNSW supervision, and therefore represent priority targets for case management, can be achieved through a multiple stage triage process that applies the Community TRAS as a screening method to determine who is referred to comprehensive follow up risk and needs assessment.

INTRODUCTION

A primary objective of offender management both in custody and in the community is to reduce individuals' likelihood of recidivism in the future. In this regard an understanding of and ability to identify correlates of reoffending risk is pivotal to corrective services research and policy. Such information allows service providers to effectively direct resources to individuals according to their likelihood of future engagement in the criminal justice system and focus interventions on those who pose the greatest risk of harm to the community.

Across Australian correctional jurisdictions the prison population has shown substantial growth over recent years (e.g. Weatherburn, Wan, & Corben, 2014). In New South Wales (NSW) and elsewhere this has corresponded with trends towards increases in the population of community-based offenders, including those subject to community based sentences in addition to offenders released from custody onto parole (Raudino, Neto, & van Doorn, 2017). Considering the substantial costs associated with construction and staffing of prisons, community sanctions may be considered a relatively inexpensive method of sentencing. However, as the caseload of community-based offenders increases there is a need for specific policies and tools that allow for efficient risk assessment and case management of these offenders with limited existing resources.

Much of the existing research on risk assessment in corrective services has focused on prison populations and return to custody in particular as the primary recidivism outcome (e.g., May, Sharma, & Stewart, 2008; Nagin, Cullen, Jonson, 2009, Piquero, Cullen, Unnever, Piquero, & Gordon, 2010, Xie et al., 2018). While return to custody is a critical outcome because it reflects extensive costs to the criminal justice system (e.g. Bakker, O'Malley, & Riley, 1998), such risk assessment approaches may not be valid for offenders completing community based orders or sensitive to other common recidivism outcomes such as future non-custodial sanctions. The aim of the current study is to describe the development of a statistical scale, named the Community Triage Risk Assessment Tool (Community TRAS), which can be used to estimate risk of return to corrective services supervision and assist relevant case management decision making for offenders currently completing orders in the community.

Community Based Orders

Community based orders are penal sanctions in which a convicted offender is permitted to remain in the community. Also defined as non-custodial sanctions, community based orders refer to any form of sanction that does not involve imprisonment, and can involve community service work; electronic monitoring; regular supervision by corrective services; fines; home detention; and good behaviour bonds or other restrictions on behaviour in the community. In jurisdictions such as NSW, offenders can also receive provisional sentences of imprisonment that are suspended (with or without supervision) on the condition that they adhere to conditions in the community.

There is a growing consensus in research and public opinion that community orders may be a more suitable option for management of offenders compared to imprisonment, both in terms of costs and effectiveness in reducing reoffending and minimising the criminogenic effects of sanctions (Barbaree et al., 2012; Cullen, Blevins, Trager, & Gendreau, 2005; Loughran et al., 2009; McAra & McVie, 2007; Piquero et al., 2010; Wilson & Hoge, 2013). In general reoffending outcomes tend to be lower for offenders completing community based orders than for those who are sentenced to custody (e.g. Villettaz, Killas, & Zoder, 2006; Killias & Villettaz, 2008). In the local context of NSW, Lulham and colleagues (Lulham, Weatherburn, & Bartels, 2009) used propensity matching to compare 6,825 offenders given a supervised bond with 7,018 offenders given a full-time prison sentence. Prison was found to exert no effect on time to re-offend amongst those who had not previously served time in custody. Offenders who had previously served time in custody, however, re-offended more quickly if they received a prison sentence than if they received a suspended sentence.

In a more extensive consideration of the literature, Villettaz and colleagues (2006) investigated 23 studies that included 27 comparisons of custodial versus non-custodial sanctions. The majority of the reviewed studies indicated that custodial sanctions were associated with increased recidivism outcomes (11 comparisons) or no difference (14 comparisons) relative to non-custodial sanctions. A similar review by Nagin et al (2009) examined 6 experimental/quasi-experimental, 11 matching, and 31 cross-sectional studies. They concluded that incarceration has a slight criminogenic effect on recidivism. The most recent systematic review by Jonson (2010) conducted a meta-analysis of 57 studies and found that the impact of a custodial compared to a non-custodial sanction was slightly criminogenic, increasing recidivism by 14 per cent.

Imprisonment may be criminogenic in the event that it disrupts existing protective factors or functioning in the community, or increases exposure to antisocial influences. The experience of imprisonment can also be characterised by privations that may exacerbate dysfunction such as victimisation, assault and isolation (e.g. Howard, Raudino, Corben, & Galouzis, manuscript in preparation; Listwan, Colvin, Hanley, & Flannery, 2010; Listwan, Sullivan, Agnew, Cullen, & Colvin, 2013). However, it continues to be a matter of study as to whether the experience of imprisonment has a measurable effect on recidivism or whether the observed outcomes are an artefact of pre-existing individual differences. For example, results from the Surveying Prisoner Crime Reduction (SPCR) longitudinal cohort study of prisoners (Cleary, Ames, Kostadintcheva, & Muller, 2012) suggested that there is a relationship between reoffending risk and the experiences offenders have of custody, such as paid employment, participation in interventions and family visits. However, these factors were no longer significant when other individual differences in risk (prior criminogenic history, individual mental health and substance abuse vulnerability) were accounted for.

Assessing risk of recidivism

A range of factors have been empirically demonstrated to be associated with future likelihood of recidivism. These can be broadly categorised as dynamic risk factors (or criminogenic needs) and static risk factors. Dynamic risk factors are those current or recent factors that may be expected to contribute to an individual's functioning or risk of offensive behaviour when in the community. Common dynamic risk factors include substance use problems, antisocial or offence supportive attitudes, antisocial peers, unemployment and financial problems, homelessness and mental health difficulties (e.g. Andrews & Bonta, 2010; Boormann & Hopkins, 2012; Cleary et al., 2012; Light, Grant, & Hopkins, 2013). Dynamic risk factors are important from an offender case management perspective because they are amenable to change through rehabilitative interventions. Conversely, many of these factors can be complex or relatively subjective to measure and therefore may be subject to error when formulating assessments of overall risk.

Static risk factors are historical, unchangeable factors that have been shown to be predictive of future likelihood of reoffending. Static risk factors can include the age or gender of the offender or the extent of their criminal history. Studies have indicated that previous offending history is the strongest single predictor of future recidivism (May at al., 2008; Ministry of Justice, 2012). Offence type has also been identified as an important indicator, with findings that offenders serving a sentence for theft, robbery, burglary are more likely to reoffend compared to those serving a sentence for violence, sexual assault or fraud offences (Brunton-Smith & Hopkins, 2013).

Static indicators of risk often provide limited information about contributing factors to offender behaviour that may inform case management, and instead act as proxies for such factors. For example, historical data that shows involvement in the criminal justice system from an earlier age may be indicative of more extensive dysfunction in the early developmental environment that drives risk such as intergenerational transmission of antisocial attitudes or behaviours from family members, socioeconomic or educational deprivations, or exposure to abuse (e.g. Hopkins, 2012; Williams, Papadopolou, & Booth, 2012). An advantage of static risk factors is that they are often readily available through formal record keeping systems and tend to be more reliable indicators of future behaviour compared to dynamic risk factors.

Assessment of risk and criminogenic needs is critical in corrective services to guide offender management decisions and intervention plans. The tools which have been developed and used in the criminal justice system range from unstructured clinical judgement; to more structured actuarial assessments involving a limited range of static factors; to more complete structured professional judgements that incorporate both clinical and actuarial techniques as well as measurement of static and dynamic risk factors.

The Level of Service Inventory – Revised (LSI-R: Andrews & Bonta, 1995) is the instrument routinely used by Corrective Services NSW (CSNSW) for assessing risk. Adopted in 1998, the LSI-R enables identification of individual risk levels and the degree of intervention required to meet that level of risk and needs. The instrument consists of 54 items over 10 domains that assess both static and dynamic factors. An overall summary risk score is produced that can be categorised into one of five risk levels for general recidivism. Higher intensity interventions, in addition to increased supervision and monitoring, can then be targeted at offenders identified as being at higher risk of re-offending. The LSI-R is therefore used to identify criminogenic needs that case management can target for intervention. It is noted, however, that assessment with the LSI-R tends to be time intensive and costly and requires extensive training of specialist staff, which can impact widespread implementation within a corrective services jurisdiction (Watkins, 2011; Xie et al., 2018).

In response to the identified administrative limitations of the LSI-R, CSNSW recently developed an actuarial tool for predicting risk of return to custody among offenders who had received a custodial sentence, named the Criminal Reimprisonment Estimate Scale or CRES tool (Xie et al., 2018). The CRES tool was developed by combining a selection of widely available historical indicators to generate an estimate of the probability by which offenders returned to custody for any reason over the following two years. Validation study showed that the CRES tool had comparable or slightly superior predictive validity when compared to the LSI-R. The CRES tool was also shown to have utility when employed in a hypothetical operational scenario to more efficiently reallocate existing LSI-R resources to offenders who are at higher risk of return to custody (Xie et al., 2018). The CRES tool has since been successfully applied by CSNSW as a method of quickly and accurately triaging offenders to more in depth assessment and case management in custody.

The Present Study

While the CRES tool represents an innovation to methods of risk assessment within CSNSW, it was developed for specialised use with offenders who were sentenced to custody only. As such it does not account for similar risk assessment and case management needs for offenders undergoing supervision in the community. The CRES tool also measures return to custody only and may not capture risk of return to other forms of corrective services supervision. In addition, it is noted that development of the CRES tool was subject to some methodological limitations including formulation of models on the basis of episode-level data as opposed to individual-level data (which may have resulted in some degree of dependence across observations), in addition to limited application of model verification methods.

The aim of the present study was to apply similar statistical techniques to the CRES tool to develop a new actuarial risk prediction measure named the Community TRAS. The Community TRAS was developed with a sample of community-based offenders supervised by CSNSW to provide an estimate of their likelihood of return to supervision in custody or the community within two years. This study also describes the results of best practice model validation analyses that aim to establish reliability of the tool across offender cohorts and over time. The development of the Community TRAS was intended to assist decision making about which offenders under community supervision should be prioritised for comprehensive risk / needs assessment, and therefore to inform selection processes about targets for case management and intervention.

METHODS

Sample

The Community TRAS model was developed using a large dataset of offenders who had commenced a non-custodial sentence involving supervision by CSNSW between July 2010 and June 2013. This generated a total sample of 39,153 offenders. As described in greater detail in the Model Validation section, the Community TRAS was initially estimated using a subsample of offenders (n = 19,623), with the remainder of the sample used in subsequent model verification (n = 9,730) and replication / finalisation (n = 9,800) analytical procedures.

It is noted that the total sample included in this study comprised unique individuals only. Over the timeframe of measurement a number of offenders were found to have more than one community-based order or episode of community supervision. In order to minimise analytical violations associated with dependence between observations, only offenders' first episode in the exposure timeframe was used in the sample.

Data

Offender and outcome variables were extracted from the CSNSW Offender Integrated Management System database (OIMS). OIMS is an operational database that is used to maintain data about all offenders under the supervision of CSNSW including demographics, historical and index offence variables, results of intake screening and other assessment, and sentence administration data. An objective of developing the Community TRAS model was to exclusively use available OIMS data so that it could be readily applied within existing operational and data collection frameworks.

Potential predictor variables were identified from a review of previous research into static factors in risk assessment, and included:

- **Demographic variables**: Gender; current age; age at first full time custodial sentence; age at first community order; age at time of most recent discharge; Aboriginal or Torres Strait Islander status; remoteness (Aria index) and socioeconomic status (Seifa index) of most recent residential location.
- **Criminal history**: Number of previous custodial episodes; total previous days in custody; previous full time custodial sentences; number of previous supervision orders; number of previous fines; number of previous periodic detention orders; interval since last custodial sentence; first offender / repeat offender status; time at large since last sentence expiry.
- **Order compliance**: Proportion of previous orders completed (ever and in the last five

years); previous non-custodial and custodial order breaches (ever and in the last five years).
- **Current order characteristics**: Order duration; type of order (supervision versus reparation and restricted movement).

In addition to including raw variables in models, theoretically meaningful calculations or combinations of variables were also considered. In particular we included the Copas rate (Copas & Marshall, 1998) which was developed to provide an index of the intensity of an offender's historical rate of recidivism and criminal justice system involvement. The Copas rate is calculated as a function of the number of previous sanctions and the interval between the current and first sanction. Inclusion of composite variables in the model has utility by increasing model parsimony and potentially addressing issues with multicollinearity and overfitting.

The outcome variable for the Community TRAS model was imposition of a new sentence resulting in custodial placement or community-based supervision by CSNSW within two years of commencement of the index community-based episode. Only return to CSNSW associated with a new conviction and sentence was included in our calculation of recidivism. The outcome variable was calculated using OIMS data on CSNSW supervision episodes.

Statistical analyses

An initial bivariate analysis of the relationship between each predictor variable and return to supervision was used to identify possible categorical and ordinal groups, dummy variables and any transformations required by continuous variables to meet linearity requirements. Associations between recidivism and each of the potential predictor variables were tested for significance using the Mantel-Haenszel chi square test for categorical predictors and analysis of variance (one way ANOVA) for continuous predictors.

Logistic regression models were then performed to examine the multivariate relationship between predictors and the outcome of interest and to provide a probability score of recidivism for each individual. To avoid problems related to statistical over control of different predictors resulting from the inclusion of multiple non-significant covariates, model fitting was conducted using both forwards and backwards methods of variable selection to identify a stable set of significant predictors (criterion $p \leq .0001$). The best predictors were retained in the final model after testing of fixed and possible interaction effects. The best model was judged by the highest likelihood ratio/degrees of freedom score. The Hosmer and Lemeshow test was then used to determine how well the model predicted any return to CSNSW. Model adequacy was also assessed using Receiver Operating Characteristic (ROC) area under the curve (AUC) statistics.

RESULTS

Table 1 shows descriptive statistics for tested predictor variables and bivariate associations with the recidivism outcome of interest. The majority of the cohort was male (81.7% *vs* 18.3%), non-Indigenous (81.1% *vs* 18.9%), less than 35 years old at the time of commencing their index episode (59.9%), and had spent a median of 181 days in prison since the start of their criminal career. The most common serious offence was *Acts Intended to Cause Injury* (29.5%), followed by *Traffic Offences* (23.2%) and *Theft and related offences* (8.3%).

Table 1. Summary of descriptive statistics for each of the predictor variables; observed distribution of returns across each level of the variable (%) or variable mean (SD) for returning offenders; and inferential statistics for the association between predictor variables and outcomes.

Predictor Variable	Mean (SD) / % (N = 39,153)	Observed return to CSNSW (N = 16,381)	Bivariate statistics (X^2/F)
Gender (Male)	81.7%	84.3%	120.4 (p≤.001)
Indigenous	18.9%	26.6%	1085.8 (p≤.001)
Age			790.5 (p≤.001)
Up to 18	4.3%	5.8%	
18-24	23.7%	26.1%	
25-34	32.0%	35.0%	
35-44	24.5%	23.7%	
45+	15.6%	9.4%	
Location Seifa index			
Disadvantaged	58.2%	43.9%	78.3 (p≤.001)
Advantaged	38.5%	39.3%	
Missing	3.3%		
Location Aria index			
Urban	63.5%	41.3%	16.5 (p≤.001)
Rural or Remote	33.2%	43.5%	
Missing	3.3%		
LSI-R risk category			
Low	14.8%	10.0%	3.1 (p≤.001)
Medium-Low	22.4%	29.6%	
Medium	20.4%	43.1%	
Medium-High	5.3%	14.9%	
High	0.8%	2.5%	
Missing	36.4%	38.2%	
Length of supervised period			
None	0.3%	0.3%	443.9 (p≤.001)
At least 12 months	77.5%	72.2%	
More than 12 months	22.2%	27.5%	
Adjusted supervision length[1]	10.6 (8.4)	12.7 (9.3)	1756.2 (p≤.001)
Time at large since last order			
None	60.3%	52.0%	343.8 (p≤.001)
Up to 6 years	28.1%	37.0%	
More than 6 years	11.6%	11.0%	
Principal Offence			
Homicide and related offences	0.1%	0.1%	3.7 (p=.05)
Acts intended to cause injury	29.5%	29.6%	
Sexual assault and related offences	1.5%	0.8%	
Dangerous or negligent acts endangering persons	3.2%	2.5%	
Abduction, harassment against the person	0.8%	0.9%	
Robbery, extortion and related offences	1.0%	1.0%	*(continued)*

[1] Supervision length continuous score / age at first community order.

Predictor Variable	Mean (SD) / % (N = 39,153)	Observed return to CSNSW (N = 16,381)	Bivariate statistics (X^2/F)
Unlawful entry with intent/burglary	3.5%	4.8%	
Theft and related offences	8.3%	11.9%	
Fraud, deception and related offences	4.6%	2.8%	
Illicit drug offences	7.1%	6.4%	
Prohibited and weapons and explosives offences	1.1%	1.4%	
Property damage and environmental pollution	4.8%	6.0%	
Public order offences	3.2%	3.5%	
Traffic and vehicle regulatory offences	23.2%	18.1%	
Offences against justice procedures	7.7%	10.0%	
Miscellaneous offences	0.2%	0.2%	
Order Type (CRES group)			
Restricted Movement	1.1%	0.8%	387.8 (p≤.001)
Reparation	21.3%	16.7%	
Supervision	77.6%	82.5%	
Age at first community order	27.6 (10.3)	24.58 (8.06)	2627.2 (p≤.001)
Age at first custodial sentence	25.68 (8.2)	24.48 (7.3)	529.4 (p≤.001)
Number prior orders	1.64 (2.66)	2.36 (3.12)	2173.9 (p≤.001)
Number prior breaches (last 5 years)	.16 (.50)	.28 (.66)	437.09 (p≤.001)
Number order completions (last 5 years)	.40 (.75)	.59 (.88)	1825.7 (p≤.001)
Number prior full time sentences	2.39 (7.21)	4.06 (9.31)	1577.3 (p≤.001)
History custodial sentence	25%	63.9%	2592.9 (p≤.001)
History community-based order	49.8%	52.3%	1749.5 (p≤.001)
First time offender	43%	26.9%	2705.8 (p≤.001)
Number prior offences (last 5 years)	1.36 (3.14)	6.07 (.94)	1153.6 (p≤.001)
Prison time lapse[2]	.48 (.79)	.69 (.86)	2155.4 (p≤.001)
Copas rate	2.36 (.26)	2.44, (.33)	2733.3 (p≤.001)
Index violent offence	35.2%	33.9%	23.708 (p≤.001)
Time spent in custody index			
None	63.2%	30%	4102.9 (p≤.001)
Low	19%	57%	
High	18%	69%	
Prior property offences (last 5 years)	12.4%	69.7%	1768.5 (p≤.001)
Prior breach of court order offences (last 5 years)	10.8%	72.2%	1798.3 (p≤.001)
Order success rate[3]	2.81 (4.5)	3.88 (4.84)	1677.5 (p≤.001)
Order failure rate[4]	1.46 (3.59)	2.56 (4.45)	2826.2 (p≤.001)

[2] SQRT of the log score of the difference between last release and first entry in prison ever.
[3] Log of number of previous order completions in the last 5 years / number of orders in the last 5 years.
[4] Log of number of previous order breaches in the last 5 years / number of orders in the last 5 years.

In the five years before commencement of the index episode, offenders had a mean of .55 previous community orders for any offence (median=0, range=0-11); a mean of .16 previous community order breaches for any offences (median=0, range=0-8) and a mean of .40 previous community based order completions (median=0, range=0-8). Finally, a total of 22,330 (57%) offenders were repeat offenders whereas 16,823 (43%) were first time offenders and did not have prior episode data entered on OIMS.

A series of logistic regression analyses were performed to generate optimal predictive estimates of the likelihood that offenders would return to CSNSW within two years. Results from the final model are summarised in Table 2; whereas the initial model was developed on a training set of 19,623 offenders, Table 2 provides the results of a logistic regression model for the entire sample (N = 39,153) for presentational purposes. A value of 1 indicates that the group of interest served as the reference category in dummy variable comparisons.

The regression models showed that after adjusting for other predictors, significant factors associated with the greatest likelihood of return to CSNSW included: Indigenous status; younger age at the time of commencing the index community episode; repeat offender status; increased number of previous offences in the past 5 years; greater duration previously spent in custody; longer community-based supervision period; and more intensive order (reparation or restricted movement compared to supervision only). Interval between last release from custody and first custodial episode was also significantly related to outcomes, indicating that as the interval between most recent release and first entry increased there was a corresponding decrease in the odds of returning to CSNSW supervision. Finally an increased Copas rate was found to have a significant positive association with odds of return. It can be seen that all predictor variables included in the final Community TRAS model had significant associations with outcomes at the criterion of p≤.0001.

Table 2. Logistic regression for the full sample model predicting return to CSNSW within two years from order commencement for offenders receiving a CBO in NSW between July 2010 and June 2013.

Measure	B (SE)	Wald Chi-square	p	OR [95% CI]
Indigenous Status				
Non-Indigenous	1			1.00
Indigenous	.42 (.02)	207.57	≤.001	1.52 [1.43-1.61]
Age				
Under 18	1			1.00
18-24	1.71 (.06)	704.27	≤.001	5.53 [4.87-6.28]
25-34	1.09 (.04)	676.66	≤.001	3.00 [2.76-3.26]
35-44	.83 (.03)	465.08	≤.001	2.29 [2.12-2.47]
45+	.50 (.03)	167.09	≤.001	1.66 [1.53-1.79]
Adjusted Length of supervision	.01 (.01)	172.64	≤.001	1.02 [1.01-1.02]
Order type (CRES Group)				
Supervision	1			1.00
Reparation / Restricted Movement	.25 (.02)	86.98	≤.001	1.29 [1.22-1.36]
Time spent in custody index				
No	1			1.00
Low-Medium	.98 (.04)	466.17	≤.001	2.68 [2.45-2.94]
High	1.03 (.04)	472.25	≤.001	2.81 [2.56-3.09]
Copas Rate	1.52 (.11)	181.47	≤.001	4.60 [3.69-5.76]
Prison Time Lapse	-.37 (.02)	177.73	≤.001	.69 [.65-.72]
Number offences (last 5 years)	.05 (.01)	78.52	≤.001	1.05 [1.04-1.07]
Repeat offender status	.42 (.03)	174.42	≤.001	1.53 [1.44-1.63]

Model discrimination

The final logistic regression model was used to develop a single value estimating the probability of an offender returning to CSNSW supervision within two years of their index community episode commencing, ranging between 0 (0% predicted probability of returning) and 1 (100% predicted probability of returning). This probability estimate comprised the basis of the Community TRAS score. To assist in use and interpretation of the tool, ranges of probabilities were also categorised into five groups indicating increasing risk of return (low = .00 - .19; medium-low = .20 – 39; medium = .40 - .59; medium-high = .60 - .79; high = .80 - .99). Table 3 shows the observed rate of return to CSNSW supervision associated with each of the five categories of the Community TRAS.

Table 3. Rate of return to CSNSW within two years by predicted probability group.

Community TRAS category	No Return	Return
1 (low)	81.3%	18.7%
2 (medium-low)	66.0%	34.0%
3 (medium)	44.1%	55.9%
4 (medium-high)	19.5%	80.5%
5 (high)	10.0%	90.0%

Model adequacy was first tested with the Hosmer-Lemeshow test. The Hosmer-Lemeshow test statistic failed to reach statistical significance, indicating that there was no significant deviation between observed and expected frequencies of return within each of the five partition groups ($\chi^2(8)$ =13.069, p=.110).

The adequacy of the model was also assessed using the AUC statistic, which plots the proportion of true positives (those predicted to return to CSNSW either in custody or community who were also observed to return) against false positives (those predicted to return to CSNSW who did not return) at any given cut-off point. As a rule of thumb, scores greater or equal to 0.9 provide 'outstanding discrimination, scores between 0.8 and 0.9 provide 'excellent' discrimination, scores between 0.7 and 0.8 provide 'acceptable or good' discrimination, whereas scores of 0.5 predict outcome at chance level (Hosmer and Lemeshow, 2000). In the current study, the AUC statistic yielded a value of 0.75, showing that the model provided good discrimination.

Model validation

Model validation is an important step that is used to assess the reliability of the model before it can be used in decision making. Model validation requires checking the model against independent data to see how well results can be replicated and therefore generalised. For validation of the Community TRAS we applied two robust model validation techniques that assess predictive accuracy for independent real and simulated samples, known respectively as cross validation and bootstrapping. Each of these techniques will be described in the following sections.

Cross validation

Cross validation is a technique for reducing bias in a model that can occur as a result of using a single training set. This involves splitting the original dataset into 3 different partitions, being the training set, the validation set and the test set (Ripley, 1996).

- **Training set:** A data set used for learning: to fit the parameters of the classifier [i.e. optimal weights][5].
- **Validation set:** A data set used to tune the parameters of the classifier [i.e. architecture, not weights].
- **Test set:** A data set used only to assess the performance [generalisation] of a fully specified classifier.

[5] The classifier refers to the algorithm used for classification of units (individuals) in the model. In the present study the Community TRAS is a type of logistic / probabilistic algorithm classifier.

After assessing the final model with the test set, the model cannot be tuned any further (Ripley, 1996). In other words: the training set is used to train the model and determine the model parameters; the validation set is used for model selection and the test set is purely for testing and generalisation ability. The test set does not guarantee the accuracy of the model; it can only say whether similar results will be obtained using the chosen model.

The cross validation process can be outlined using the following steps: 1) randomly divide all the available data into training (50%), validation (25%) and test (25%) sets; 2) select architecture of the model and training parameters with logistic regression methodology; 3) train the model using the training set; 4) use the parameters from the training set to predict the model in the validation set; 5) repeat steps *2* through *4* using different architectures and training parameters until a satisfactory fit is achieved; 6) select the best model and train it using data from the training and validation sets and 7) assess the final model using the test set with no further changes.

Table 4 reports the proportion of the outcome distribution for each of the training (n = 19,623), validation (n = 9,730) and test (n = 9,800) dataset partitions used in validation of the Community TRAS, in addition to goodness of fit statistics and percentages of individuals correctly predicted by the model for each dataset partition. Finally the AUC statistic has been reported to show the discriminative accuracy of the Community TRAS for each of the dataset partitions. It can be seen that findings from this cross validation procedure were highly comparable and yielded similar results.

Taken together, the results of the cross validation analysis showed that the Community TRAS was generalisable or showed similar performance and outcomes across each of the dataset partitions. The high degree of comparability across datasets indicates that parameter values in the Community TRAS, as developed in the initial training set, behaved consistently for different samples and confirms the structure and architecture of the model.

Table 4. Results from the cross validation method of model validation.

Dataset	Return to CSNSW	Nagelkerke pseudo R^2	Correctly Predicted	AUC
Training	41.9%	.238	71.6%	.75
Validation	41.8%	.230	69.8%	.74
Test	42.1%	.233	70.3%	.75

Bootstrapping

Bootstrapping was employed as a second model validation approach for the Community TRAS. Bootstrapping is a resampling technique that replicates the process of sample generation from an underlying population by drawing multiple random samples with replacement from the original dataset. Testing the model on the multiple samples can then be used to assess the degree to which the estimated regression coefficients would be likely to vary across other random samples of the same population. As such, results can be replicated over time and findings can be generalised in the absence of multiple samples of unique data. Moreover, if a sample is representative of the target population (in this case offenders), bootstrapping also accounts for error associated with multiple statistical tests by yielding an empirical sampling distribution for each coefficient.

For the purpose of the present study, simulations were repeated 5,000 times using the same samples of size *N*. A logistic regression model (the predictive model in Table 2) consisting of a previously specified set of 9 predictors was fitted in each sample for 5,000 replications. The estimated regression coefficient, the averaged (bootstrapped) standard error and 95% confidence interval (CI bias) based on the empirical sampling distributions created by bootstrapping for 5,000 replications has been reported in Table 5. These confidence intervals depict the range of plausible regression coefficients one might encounter from other random samples.

From Table 5 it can be seen that the model coefficients and confidence intervals for those coefficients are closely aligned for Community TRAS results estimated from the original sample and from the bootstrap. The standard errors (SE) for each coefficient (B) and the 95% confidence intervals had small ranges, as can be expected given the large samples involved. The performance in the bootstrap sample represents estimation of the apparent performance, and the performance in the original sample represents test performance. The difference between these performances is an estimate of the optimism in the apparent performance. In the present study, the difference between apparent and test performance was negligible, which suggests that the model can be replicated with a high degree of optimism.

Table 5. Comparison of model coefficient statistics for the predictive model (left hand panel) and the average of model coefficient statistics derived from bootstrapping (right hand panel).

	Predictive Model				Bootstrapped Model			
	Coefficient		95% CI		Coefficient		95% CI	
Measure	B (SE)	p	Lower	Upper	B (SE)	p	Lower	Upper
Intercept	-.32 (.01)	≤.0001	-	-	-.32 (.01)	≤.0001	-	-
Indigenous Status								
Non-Indigenous	1							
Indigenous	.42 (.02)	≤.0001	1.43	1.61	.42 (.02)	≤.0001	1.43	1.61
Age								
Under 18	1							
18-24	1.71 (.06)	≤.0001	4.87	6.28	1.71 (.03)	≤.0001	4.90	6.25
25-34	1.09 (.04)	≤.0001	2.76	3.26	1.09 (.04)	≤.0001	2.75	3.25
35-44	.83 (.03)	≤.0001	2.12	2.47	.83 (.03)	≤.0001	2.13	2.47
45+	.50 (.03)	≤.0001	1.53	1.79	.50 (.03)	≤.0001	1.53	1.79
Adjusted supervision length	.01 (.01)	≤.0001	1.01	1.02	.01 (.01)	≤.0001	1.01	1.02
Order type (CRES Group)								
Supervision								
Reparation / Restricted Movement	.25 (.02)	≤.0001	1.22	1.36	.25 (.02)	≤.0001	1.22	1.36
Gaol previous days								
None	1							
Low	.98 (.04)	≤.0001	2.45	2.94	.98 (.04)	≤.0001	2.46	2.93
High	1.03 (.04)	≤.0001	2.56	3.09	1.03 (.05)	≤.0001	2.56	3.11
Copas Rate	1.52 (.11)	≤.0001	3.69	5.76	1.52 (.18)	≤.0001	3.20	6.69
Prison time lapse index	-.37 (.02)	≤.0001	.65	.72	-.37 (.03)	≤.0001	.64	.73
Number offences (past 5 years)	.05 (.01)	≤.0001	1.04	1.07	.05 (.01)	≤.0001	1.04	1.07
Repeat offender status	.42 (.03)	≤.0001	1.44	1.63	42 (.03)	≤.0001	1.43	1.63

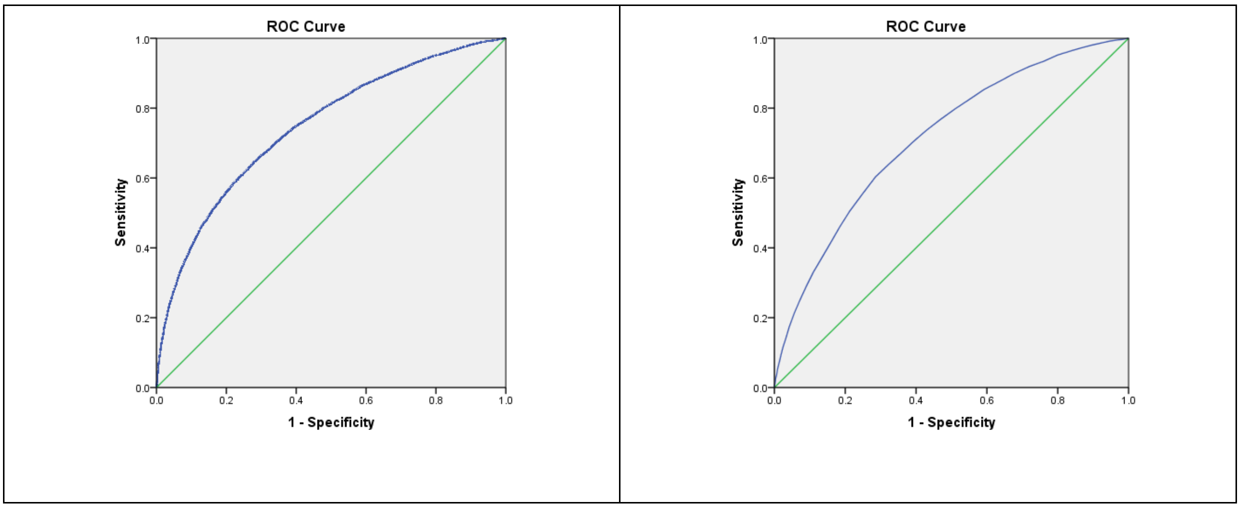

Figure 1. Plots showing the area under the curve (AUC) for the predicted probabilities group from the predictive regression model (left hand panel) and the LSI-R assessment (right hand panel).

In summary, the employed methodologies for development of the test model and for model validation led to similar conclusions. It is therefore reasonable to expect that the predictive model underlying the Community TRAS can be replicated and generalised to other independent samples.

Model applicability

As described earlier, ROC analyses for the five category model of the Community TRAS yielded an AUC statistic of .75, indicating good discriminative accuracy. To compare the Community TRAS to current CSNSW practice, ROC analyses were also conducted for all offenders in the current sample who had an LSI-R completed during their index episode (n = 24,919)[6]. Results for the five level categorisation of the LSI-R yielded an AUC value of .71 for prediction of return to CSNSW supervision within two years. This indicates that the Community TRAS delivered comparable or slightly better discriminative accuracy compared to the LSI-R. Figure 1 shows the ROC curves for both the Community TRAS and the LSI-R.

We also examined whether the Community TRAS could have operational utility by improving allocation of more in-depth LSI-R assessments to those offenders who are more likely to reoffend and return to CSNSW supervision. As a result of resource demands and other operational considerations, only a subset of community-based offenders currently receive an LSI-R assessment and the remainder do not receive an estimate of risk (36% of the current sample did not have an LSI-R assessment). Prioritisation of limited LSI-R and risk assessment resources may be improved by using the Community TRAS as a screening tool to identify those offenders who are more likely to be a target for intervention.

Figure 2 (left panel) shows that in the study sample, 6,255 offenders without a LSI-R returned to supervision (44% of those without an LSI-R). In contrast, 14,793 offenders with a LSI-R did not return (59.4% of those with a valid LSI-R). This indicates that the degree of correspondence between administration or non-administration of the LSI-R and that offender's likelihood of return to CSNSW supervision is close to chance.

[6] It is noted that 36% of the sample was missing data on LSI-R administration. Offenders under supervision by CSNSW often do not receive an LSI-R assessment for reasons that may be associated with risk of recidivism (e.g. short sentence length). To address this we examined the effect of selection bias associated with missingness of LSI-R data on the final Community TRAS model (see Appendix A), which was not observed to impact performance. We concluded that selection bias associated with patterns of missing LSI-R was unlikely to have substantially influenced the results of model applicability analyses reported in this section.

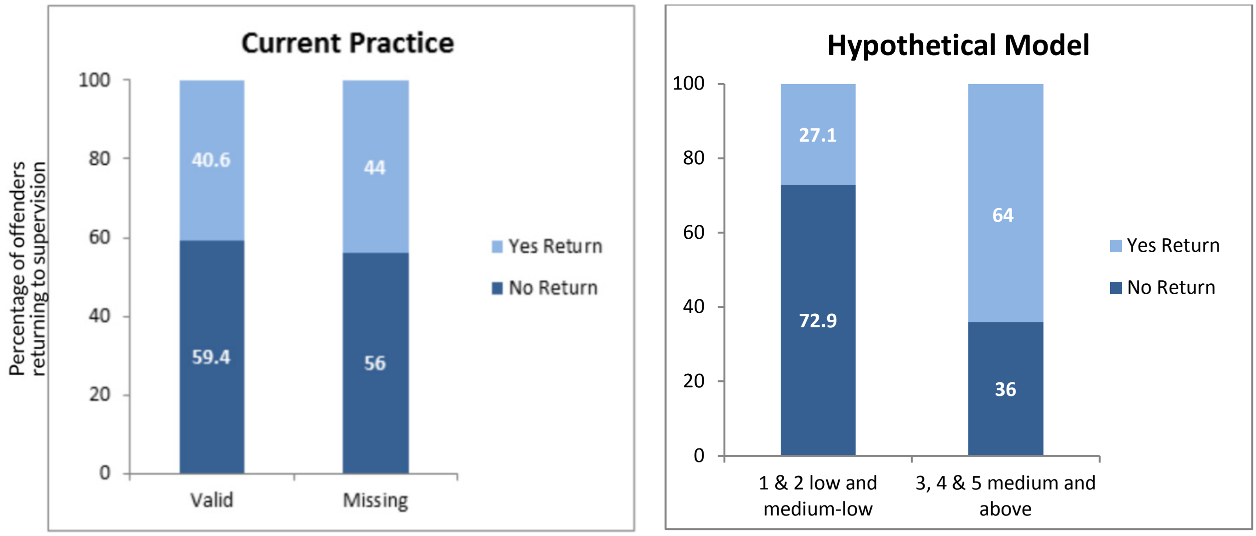

Figure 2. Comparison between the current practice of LSI-R administration (valid assessment vs missing assessment) and the study model as a screening tool (LSI-R delivered to medium and above only: low and medium-low versus medium, medium-high and high (1,2- 3,4,5) by return to CSNSW supervision within 2 years.

A related consideration is that of those 14,793 offenders who received an LSI-R assessment and did not return to supervision, the vast majority (71.3%; n = 10,548) were categorised as being in the low or medium-low categories of risk. Conversely only 4,245 offenders (28.7%) were classified in the risk priority categories of medium or above. There is the implication that more efficient allocation of LSI-R assessment resources may be achieved by screening out those low risk offenders who are unlikely to return to supervision prior to engaging in the assessment process.

In order to achieve this, we subjected the Community TRAS to a series of simulations to identify a single screening cut-off point that achieved the optimal ratio of sensitivity and specificity in accordance with signal detection principles (see Appendix B). For the purposes of this study we selected a Community TRAS score of .4 as the threshold, so that offenders in the first two categories (low, medium low) would not be deemed a priority for receiving the LSI-R and offenders in the latter three categories (medium, medium-high, high) were prioritised for further assessment.

Figure 2 shows the observed reoffending rates under the hypothetical scenario where offenders with a Community TRAS score under .4 did not receive LSI-R assessment and those with a Community TRAS score of .4 or above did receive an LSI-R assessment (right panel). Compared to the current method of allocating LSI-R assessments (left panel) it can be seen that this screening method had substantially greater discrimination in allocating LSI-Rs to offenders who were at risk of offending. Under this hypothetical model 72.9% of offenders who did not meet screening criteria for an LSI-R assessment did not return to supervision and were therefore correctly identified as low risk or priority for intervention. Further, 64% of offenders who did meet screening criteria for LSI-R assessment did return to supervision, which is in contrast to the 40.6% of offenders who received an LSI-R assessment under current practice and returned within two years.

Table 6 also shows the percentage of all offenders with a valid LSI-R assessment classified accordingly to the five risk categories under current practice and under conditions of the hypothetical model.

Table 6. Comparison between existing LSI-R and hypothetical model classifications made for all offenders with a valid LSI-R (n = 24,919).

Risk Category	LSI-R	Hypothetical model
Low	23.2%	26.7%
Medium Low	35.2%	32.7%
Medium	32.1%	28.8%
Medium High	8.3%	9.7%
High	1.2%	1.9%

DISCUSSION

As the population of offenders undergoing supervision in the community increases (e.g. Raudino et al., 2017), there is a corresponding need for tools to assist in identifying offender risk and allocating limited resources to priorities for case management and intervention. The aim of this study was to develop a predictive model of recidivism (defined here as any return to CSNSW within two years) for offenders undergoing community-based supervision with CSNSW. This model, which resulted in the formulation of a predictive tool named the Community TRAS, was developed from a set of static or historical predictor variables that were readily available within existing offender management databases, with the intention of being capable of producing quick and accurate estimates of offender risk at the time of entering supervision.

In line with previous research (Copas & Marshall, 1998; May et al., 2008; Smith & Jones, 2008; Xie et al., 2018), the results showed that a limited set of historical variables can derive accurate estimates of offender risk. Significant predictors were largely associated with history of offending behaviour and involvement in the criminal justice system, including the age at which the offender commenced offending behaviour; the Copas rate (Copas & Marshall, 1998) or intensity of the offenders' criminal history; prior imprisonment; and type and length of sentence imposed at the current episode. Indigenous cultural status was also a significant predictor of our measure of recidivism. It should be noted that in an actuarial model such as the Community TRAS, predictor variables serve as statistical proxies for variance between individuals and their risk of recidivism and may not be interpreted as theoretically meaningful. In particular, the results do not provide any information about meaningful causal relationships between Indigenous status and criminal justice outcomes.

Whereas previous research has focused on predictive models for imprisoned samples and for reimprisonment outcomes (e.g. Xie et al., 2018), this study shows that satisfactory predictive accuracy can also be achieved for offenders serving community-based orders and for the outcome of reconviction that warrants return to any supervision under corrective services. This definition of outcome is advantageous because it has clear implications for prioritising offenders on the basis of their estimated future burden on the criminal justice system (both in terms of community safety and community resources), and may serve to establish a threshold for seriousness of recidivism outcomes that reduces focus on more minor reoffending outcomes that warrant unsupervised sanctions such as fines.

ROC analyses indicated that the Community TRAS had discriminative accuracy (AUC = .75) that was comparable or stronger compared to current practice involving administration of the LSI-R to the target sample (AUC = .71). It has been previously observed that rates of accurate prediction for recidivism is rarely likely to exceed around 75% in the event that the actual recidivism rate is 50% (Raynor, Kynch, Roberts, & Merrington, 2000). In this regard the Community TRAS represents a model that approaches optimal accuracy within the standard constraints of prediction of recidivism, and may improve the accuracy of estimation for some forms of recidivism compared to the more resource-intensive current method of risk assessment used by CSNSW.

Our use of best practice methods of model verification such as cross validation and bootstrapping also indicated that the Community TRAS showed consistency in performance across different (both real and simulated) samples. This outcome has important operational implications because it suggests the tool may be robust to changes in offender population characteristics and therefore reliable over time. Nonetheless, it would be beneficial if implementation of the Community TRAS was accompanied by ongoing study to monitor predictive validity and recalibrate model weights where required.

An intended operational usage of the Community TRAS is to assist in decision making about which offenders should be prioritised for more in depth assessment with the LSI-R and other case management. The results of this study indicated that a Community TRAS score of .4 (or risk category 3 and above) achieves an optimal balance between sensitivity and specificity in discriminating offenders from non-offenders. Application of this score as a screening threshold can substantially improve allocation of LSI-R assessments to those offenders who are more likely to return within two years. While the selected cut-off of .4 was derived from multiple modelling simulations to identify optimal discrimination accuracy, it is noted that judicious variation of this threshold may be applied to reflect policies or priorities relating to detection of at-risk offenders or allocation of limited available case management resources to a growing offender population.

Limitations

The Community TRAS was developed to predict recidivism in reference to specific outcomes relating to any return to CSNSW (either through reimprisonment or a supervised community-based order) following reconviction. As a result it may not be sensitive to reoffending outcomes that do not result in the imposition of imprisonment or a supervised order. Like most measures of recidivism, the tool is also unable to account for offensive behaviour that does not result in detection and prosecution in the courts (e.g. Morris, Reilly, Berry, & Ransom, 2003). On the other hand, the Community TRAS is intended to predict return associated with any reoffending among a heterogeneous population of offenders, and it is unclear whether the tool can achieve comparable predictive accuracy for certain subgroups of offenders or types of reoffending such as sexual or domestic violence reoffending.

The results of this study indicated that repeat offender status, or whether the individual had engaged in supervision with CSNSW prior to the index episode, is a critical predictor of recidivism. However, the Community TRAS was developed on the basis of information derived from the offender's adult criminal history only and data about their juvenile justice outcomes were not available. The tool was intended to be derived from readily available CSNSW data and this does not include the majority of court or supervision episodes when the individual was in their adolescence. Future research may improve on the predictive validity of similar models by linking interdepartmental data streams that are relevant to criminal history. It is likely that other important sources of variance in recidivism outcomes were also not available on OIMS and therefore not included in the predictive model.

Lastly, it is noted that while the Community TRAS was found to have comparable or superior predictive accuracy for our recidivism variable of interest compared to the LSI-R, it is not intended to supplant the LSI-R in current practice. The Community TRAS was developed on the basis of historical variables that provide limited meaningful information about causal contributors for that offender's risk or targets for intervention. In contrast, the LSI-R is a more comprehensive assessment that combines both static predictors with information about criminogenic needs and responsivity factors, resulting in a greater depth of insight into the offender's targets and modalities for intervention. While there may be a statistical rationale for deferring to Community TRAS scores as opposed to LSI-R total scores as the primary measure of overall risk, there is an ongoing need for LSI-R or other assessments to inform qualitative components of case plan formulation. This underpins the operational utility of applying actuarial tools, such as the Community TRAS, that are accurate and efficient but nonetheless guide referral to additional assessment processes.

Conclusion

The aim of this study was to develop an actuarial tool to quickly and accurately discriminate risk of recidivism among community-based offenders. The results showed that the Community TRAS has good discriminative accuracy and can be reliably used to assign offenders to categories of risk in a similar manner to current CSNSW practice using the LSI-R. Model validation techniques also showed positive indications of stability in regards to the predictive validity of the tool across samples.

A clear operational advantage of the Community TRAS is that it uses readily available information entered into existing databases on offenders under supervision, allowing for the development of automated processes of risk estimation for all offenders in the target population. While the results of this study indicate that such advantages can be applied to improve efficiencies in the assessment process, it is important to reiterate that the Community TRAS is intended to be used in conjunction with other assessments such as the LSI-R to provide a comprehensive understanding of offenders' risk and case management needs.

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(Appendices to follow)

APPENDIX A

The Community TRAS was developed with all offenders under community supervision between July 2010 and June 2013 regardless of whether they had been administered an LSI-R. The model may therefore perform differently when applied only to those offenders who had a valid LSI-R attached to their index episode. This may in turn have influenced the results of some analyses conducted in the study that required valid data relating to both the Community TRAS and the LSI-R (see Model Applicability). In the following section we tested this possibility by comparing sample differences and Community TRAS performance outcomes for those offenders with and without a valid LSI-R.

The first step of analysis was to compare offenders who had and had not completed an LSI-R on key variables that were featured in the final Community TRAS predictive algorithm. Results (Table 1A) indicated that offenders who received an LSI-R assessment were significantly more likely to serve an order with restricted movement or reparation; have a shorter duration of supervised order; and have a lower number of unsuccessful previous order completions compared to those who did not receive a LSI-R assessment. Those offenders with a current LSI-R were also more likely to be serving a current sentence for acts intended to cause injury, sexual offences, offences against justice proceedings, robbery and drug offences. There were no significant differences in terms of Copas rate, previous history of custodial or non-custodial sentences or reoffending status.

Table 1A. Bivariate comparisons between offenders with a current valid LSI-R and those without a valid LSI-R.

Measure	Valid LSI-R (N=24,919)	Missing LSI-R (N=14,234)		
	Mean (SD)/%	Mean (SD)/%	F/X²	p
Sex (Male)	81.4%	82.3%	4.61	.03
Age	33.12 (11.2)	32.31 (10.5)	49.35	≤.0001
Order (Restricted Movement / Reparation)	42.9%	10.8%	5364.45	≤.0001
Age at first community order	27.89 (10.6)	27.22 (9.8)	38.09	≤.0001
Number community order failures (last 5 years)	.14 (.48)	.17 (.53)	21.01	≤.0001
Current offence				
Acts intended to cause injury	31.5%	26.2%	117.90	≤.0001
Sexual offence	2.0%	0.8%	73.46	≤.0001
Traffic offence	20.1%	28.6%	370.94	≤.0001
Government offence	8.1 %	7.1%	11.28	.001
Abduction offence	0.7%	0.9%	6.98	.005
Robbery offence	1.2%	0.7%	17.01	≤.0001
Burglary offence	3.8%	3.1%	12.35	≤.0001
Fraud offence	3.9%	5.8%	80.02	≤.0001
Drug offence	7.9%	5.8%	56.65	≤.0001
Prior property offences (last 5 years)	12.0%	13.0%	8.87	.002
Prior order breaches (last 5 years)	10.4%	11.5%	11.35	≤.0001
Any prior full time custody	24.6%	25.6%	4.23	.02
Supervision length	10.4 (8.50)	10.99 (8.30)	42.97	≤.0001
Adjusted order breach rate (last 5 years)	.29 (.35)	.32 (.36)	27.76	≤.0001

Given evidence of significant differences between offenders with and without an LSI-R, we examined the extent to which related selection biases influenced performance of the Community TRAS. To do this we estimated an index of selection bias which was then included in the final model of the Community TRAS (as originally depicted on Table 2) as a covariate. Estimation of selection bias was achieved by the use of a Heckman correction (Heckman & Robb, 1986). This correction involved computing a sample selection hazard score λ for each offender which represents their conditional probability of having a valid LSI-R. The predictors used in the calculation of the hazard included the risk factors which have been found to differ among the two groups of offenders with and without a valid LSI-R assessment (the factors are those reported in Table 1A with a selected criterion of p< 0.001). The estimated hazard λ for each respondent was then incorporated into the regression models in Table 2A to control for selection bias.

Comparison of results before and after adjustment for sample selection hazard scores revealed that the conclusions drawn from both sets of findings were similar. Specifically, while some coefficients were reduced slightly after adjusting for selection bias, the p values and effect sizes of coefficients remained comparable. The observed consistency in weightings of key variables before and after adjusting for selection bias indicates that the performance of the Community TRAS was unlikely to have been influenced by changes in sample composition based on completion of an LSI-R.

Table 2A. Coefficients and standard errors for each predictor in the Community TRAS model before and after adjustment for the selection bias hazard score.

Measure	Adjusted for covariates		Adjusted for covariates and Selection bias	
	B (SE)	P	B (SE)	p
Intercept	-.32 (.01)	≤.001	-.32 (.01)	≤.001
Indigenous status				
Non-Indigenous	1		1	
Indigenous	.42 (.02)	≤.001	.41 (.02)	≤.001
Age at beginning of current COB episode				
Under 18	1			
18-24	1.71 (.06)	≤.001	1.67 (.06)	≤.001
25-34	1.09 (.04)	≤.001	1.06 (.04)	≤.001
35-44	.83 (.03)	≤.001	.80 (.03)	≤.001
45+	.50 (.03)	≤.001	.49 (.04)	≤.001
Adjusted Length of supervision	.01 (.01)	≤.001	.02 (.01)	≤.001
Order type Cres Group				
Supervision				
Reparation + Restricted Movement	.25 (.02)	≤.001	.25 (.02)	≤.001
Gaol previous days				
No	1		1	
Low-Medium	.98 (.04)	≤.001	.98 (.04)	≤.001
High	1.03 (.04)	≤.001	1.02 (.04)	≤.001
Copas Rate	1.52 (.11)	≤.001	1.52 (.11)	≤.001
Prison Time Lapse	-.37 (.02)	≤.001	-.36 (.02)	≤.001
All crime previous 5 years	.05 (.01)	≤.001	.05 (.01)	≤.001
Repeat offender status	.42 (.03)	≤.001	.42 (.03)	≤.001

APPENDIX B

As a part of a model's discrimination accuracy, the decision of where to select a cut-off point or threshold is governed by a reasonable compromise between sensitivity and specificity. Sensitivity refers to true positive rate or the probability that a predicted positive outcome (in this case recidivism) is the same as the observed outcome. Specificity refers to the correct rejection rate or the probability that a predicted negative outcome (in this case no recidivism) is the same as the observed outcome. For example, ROC curve analysis considers all consecutive cut-offs points for discrimination accuracy as a function of rates of true positives and false positives (the inverse of correct rejections).

Determination of an optimal cut-off point may be informed by both data driven and utility-based considerations. In the operational context of CSNSW, prioritisation of sensitivity may increase the risk of false positives (e.g. completing LSI-R assessments for offenders who do not reoffend). In this case the harm associated with over-assessment and loss of time and resources is offset by the benefits associated with true positives (assessment of and intervention with offenders who do reoffend). On the other hand, a cut-off that prioritises specificity can have the benefit of saving LSI-R resources by optimising correct rejection of offenders who do not return to CSNSW. However, this may correspondingly increase the harms associated with false rejections, whereby offenders who are at risk of recidivism do not undergo further assessment and intervention.

For the purposes of the present study, a range of cut-off points were estimated for the Community TRAS and tested based on the harm / benefit approach. As opposed to applying specific utility-based decision making we opted to identify and apply a data driven cut-off point that statistically optimised both sensitivity and specificity.

Table 1B shows discrimination accuracy statistics for a number of selected cut-off points. The positive likelihood ratio (+LR) measures the extent to which a positive predicted outcome (score above the cut-off) increases the likelihood that an offender will come back to the system; the negative likelihood ratio (-LR) measures the extent to which a negative predicted outcome (score below the cut-off) decreases the likelihood that an offender will not return to the system. The diagnostic odds ratio is a measure of the effectiveness of a diagnostic test, defined as the ratio of the odds of the test being positive if the subject reoffends relative to the odds of the test being positive if the subject does not reoffend. The diagnostic odds ratio ranges from zero to infinity, although for useful tests it is greater than 1, with higher diagnostic odds ratios indicating better test performance.

Among the selected cut-off points shown in Table 1B, a score of .38 represents the most consistent balancing of robust sensitivity and specificity in addition to a high diagnostic odds ratio. Whereas other cut-offs may be selected based on operational priorities for detecting at-risk offenders (e.g. .20) or saving resources (e.g. .42), the optimal cut-off maximises both of these priorities without liberal or conservative criterion bias.

Table 1B. Sensitivity and specificity statistics for a selection of tested cut-off points.

Cut-off Point	Sensitivity	Specificity	+LR	-LR	Diagnostic Odds ratio
.42	.69	.78	3.04	0.43	7.09
.38	.73	.71	2.58	0.38	6.75
.30	.75	.61	1.91	0.43	4.49
.20	.92	.28	1.28	.029	4.00

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Research Bulletin No. 38
ISSN 2207 0850

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