

# **Research Bulletin**

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# The Custody Triage Risk Assessment Scale (Custody TRAS): An updated statistical model for predicting risk of return to custody

### Alessandra Raudino, Simon Corben, Jennifer Galouzis, Yatin Mahajan, & Mark Howard

#### Aims

This study reports on the development of an actuarial risk assessment tool named the Custody Triage Risk Assessment Scale (Custody TRAS). The Custody TRAS allows users to predict the risk that a custody-based offender will return to custody under a new sentence within two years of release.

#### Methods

A total of 21,089 offenders released from full time custody between January 2011 and December 2014 served as the study sample. Logistic regression modelling using various predictor variables was used to construct optimal predictive models, which were then tested using bootstrapping and other model validation techniques.

#### Results

Significant predictors of return to custody included age; density of custodial episodes over time; previous non-custodial convictions for offending; Indigenous status; and interval since last custodial episode. The resultant Custody TRAS predictive model was found to have satisfactory stability across samples, and comparable or better discriminative accuracy for offenders' return to custody compared to the Level of Service Inventory – Revised (LSI-R). Additional signal detection analyses indicated that a cut-off of .20 on the Custody TRAS allowed for robust discrimination between offenders who did and did not return to custody with a new sentence within two years.

#### 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 Custody TRAS as a screening method to determine who is referred to comprehensive follow up risk and needs assessment.

### INTRODUCTION

There has been a sizeable growth in the prison population across Australia in recent years, with an increase of 3.8% of offenders in full-time custody from 2017 to 2018 (Australian Bureau of Statistics, 2018). The adult prison population is highest in New South Wales (NSW), accounting for 32% of the total Australian prison population at the end of the 2017-2018 financial year. In NSW the number of offenders in custody has grown by 4.1% in 12 months until June 2018, and is expected to increase further in the following years (NSW Bureau of Crime Statistics and Research, 2018).

Growth in the prison population not only influences the substantial costs associated with prison infrastructure, but also has implications for resourcing and operation of offender case management processes. Strains on offender management resources and increasing growthrelated demand are exacerbated by high rates of adult recidivism in NSW (NSW Bureau of Crime Statistics and Research, 2017) and increasing concentration of higher risk offenders who have complex intervention needs in custody (e.g. Howard & Corben, 2018; 2019).

In light of recent trends there is an increasing need for efficiency in case management processes that address offenders' recidivism risk, with attendant effects on the social and economic burdens of reoffending and reimprisonment. In accordance with the risk principle of the Risk Need Responsivity (RNR: Andrews & Bonta, 2010) model of correctional intervention, effective case management is critically guided by assessment of an offender's likelihood of recidivism. To this end, the present study reports on the development of an automated risk assessment tool named the Custody Triage Risk Assessment Scale (Custody TRAS), which uses readily available data to estimate an offender's probability of return to custody under a new sentence within two years of release. It is intended that the Custody TRAS can facilitate decision making at the population level around allocation of custody-based offenders to more comprehensive assessment, case management and intervention.

#### **Risk Assessment**

Factors that are empirically associated with the likelihood of recidivism can be broadly divided into categories of dynamic and static risk. Dynamic risk factors (also known as criminogenic needs) are potentially changeable factors that have a causal relationship with reoffending such as substance abuse, negative peer associations, antisocial or offence supportive attitudes, unemployment and financial problems, homelessness and mental health difficulties (Andrews & Bonta; 2010; Boormann & Hopkins, 2012; Light, Grant, & Hopkins, 2013). Dynamic risk factors are often complex and difficult to measure, and therefore may be subject to measurement error. However, because these factors are amenable to change and routinely targeted in evidence-based are interventions, they are considered critical subjects of assessment from a case management perspective.

contrast. static risk factors comprise In unchangeable features of the individual's history and characteristics including their age, gender, and prior criminal behaviour. Static factors such as criminal history and age are among the strongest predictors of future recidivism (Jones, Hua, Donnelly, McHutchison, & Heggie, 2006; Holland, Pointan, & Ross, 2007; May, Sharma, & Stewart, 2008), and therefore add substantial predictive power to assessments of risk. Static factors are often readily accessed through formal records and are more likely to be standardised in reporting, relative to dynamic risk factors. However, a disadvantage of static risk assessments is that they provide limited information about dynamics of the individual's case management needs, other than required intensity (Andrews & Bonta, 1995; 2010).

For a number of years the primary method of assessing both an offender's likelihood of general reoffending and their dynamic risk factors within Corrective Services New South Wales (CSNSW) has been the Level of Service Inventory - Revised (LSI-R: Andrews & Bonta, 1995). The LSI-R consists of 54 items covering multiple domains of both static and dynamic risk factors. As a result, the assessment allows for estimation of overall risk of general recidivism as well as identification of criminogenic needs. In the context of CSNSW, LSI-R assessments are used to determine offenders' priority for various interventions and the intensity of case management, tailored to their individual needs as identified in the domains of dynamic risk (e.g. Watkins, 2011).

While the LSI-R has the substantial benefit of incorporating assessment of both general risk and criminogenic needs, it confers a number of logistical barriers to efficient case management of inmates at the population level. Completion of assessments is often a time and resource intensive task, requiring multiple corroborating streams of evidence and scoring by specially trained staff (Watkins, 2011; Xie et al. 2018). The implications of these barriers are particularly pronounced in the corrections context, given the time-sensitive nature of case management for offenders who often have relatively brief windows of opportunity for intervention during shorter sentences.

To address these issues, Xie and colleagues (2018) developed a tool for predicting recidivism risk among CSNSW inmates, named the Criminal Reimprisonment Estimate Scale (CRES). The CRES tool consists of a small number of readily available static factors that may be used to automatically generate an estimate of any individual inmates' likelihood of any return to custody within two years. The tool was intended to facilitate effective triaging of limited case management resources by identifying higher risk offenders so that they could be prioritised for further assessment and intervention. Validation analyses indicated that the CRES tool had similar or slightly better accuracy in predicting return to custody compared to the LSI-R total risk score.

Following from the example of the CRES, Raudino and colleagues (Raudino, Corben, van Doorn, & Galouzis, 2018) developed a second actuarial tool to predict recidivism outcomes among offenders under supervision in the community. Named the Community Risk Assessment Triage Tool (Community TRAS), this assessment uses readily available static risk factors to predict the probability of an offender returning to CSNSW with a reconviction within two years. Advanced model verification and validation methods (including cross-validation and bootstrapping techniques) used in this study indicated high reliability and stability of the Community TRAS.

#### The Present Study

The existing CRES tool represents a significant innovation in how inmates can be assessed and allocated to case management processes within NSW correctional centres. Validation analyses also confirmed that measures such as the CRES tool can rapidly and efficiently assess risk while maintaining similar or better predictive discrimination compared to more resource intensive assessments (Xie et al., 2018).

However, it is noted that development of the CRES tool was subject to some methodological limitations. For example, recidivism was defined as any return to custody, including conviction for reoffending in addition to parole or other order violations. This definition of recidivism may arguably not be optimal for prioritising case management resources in accordance with the risk principle, and may also be prone to instability as community supervision practices change over time. The CRES tool also underwent only limited model verification procedures to assess reliability across offender cohorts. The present study expands on previous development of the CRES tool and the Community TRAS by constructing an updated model for assessing recidivism risk among inmates serving custodial sentences in NSW. This model, named the Custody Triage Risk Assessment Scale (Custody TRAS), applies similar statistical models to estimate likelihood of return to custody with a new sentence (with or without balance of parole) within two years of release. In addition to developing the predictive model itself, this study utilises best practice model validation techniques to test model reliability and examine potential thresholds that may be optimally applied to guide decision making about further case management.

## **METHODS**

#### Sample

The total sample employed in development of the Custody TRAS included all offenders who were released from NSW correctional centres between January 2011 and December 2014 (N = 21,089). Among all offenders in the sample, 8,340 (39.4%) returned to custody with a new sentence within two years. A further 1,220 offenders (5.8%) returned to custody for breach of parole only and were not reconvicted within two years. The remainder (54.3%; 11,449) did not return to custody under any circumstances over the two years following release.

#### Data

Offender and outcome variables were retrieved from the CSNSW Offender Information Management System (OIMS). OIMS is an operational database that maintains data on all offenders under supervision by CSNSW and includes information on offender demographics, historical and current offences, results of assessment, and other case management and administrative processes. Only data retrieved from OIMS were considered as potential predictors in the Custody TRAS model, in accordance with aims to develop a method of assessing risk that could be efficiently incorporated into existing data streams and reporting systems.

Based on a review of existing research, the following static variables were identified as potential predictors of recidivism and relevant data were extracted from OIMS:

- Demographic variables: Age at the time of custodial episode start; gender; Aboriginal or Torres Strait Islander status;
- Criminal history: Intensity of previous custodial episodes (represented by a modified Copas rate, or the number of prior prison episodes divided by the difference in age between first and current episode: see Copas & Marshall, 1998); number of previous noncustodial sentences; time in the community since most recent release from custody;
- Current custodial episode: Current most serious offence for violence (ANZSOC divisions 1, 2, or 4<sup>1</sup>) or robbery / theft (ANZSOC divisions 6, 7, 8, or 9<sup>2</sup>); type of current custodial episode (whether or not the offender was in custody to serve balance of parole only); release to parole following release from the current custodial episode.

The outcome variable for the Custody TRAS model was return to the custody with a new sentence or a new sentence in addition to balance of parole. The outcome variable was calculated from OIMS as the first sentence date resulting in a custodial sanction that was registered following release from the index custodial episode. Instances of return to custody were censored at two years

<sup>&</sup>lt;sup>1</sup> (1 = Homicide and related offences; 2 = Acts intended to cause injury; 4 = Dangerous or negligent acts endangering persons).

<sup>&</sup>lt;sup>2</sup> (6 = Robbery, extortion; 7 = Unlawful entry with intent/burglary, B&E; 8 = Theft and related offences; 9 = Fraud, deception and related).

following release from the index custodial episode and any later instances of return were not considered when calculating recidivism outcomes.

#### **Statistical analyses**

Initial exploratory analyses of the bivariate relationships between potential predictor variables and return to custody outcomes were 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 for continuous predictors.

A series of logistic regression models were then conducted to examine the multivariable relationships between predictors and the outcome variable, and to generate estimates of probability of recidivism for each offender. To overcome any problems related to statistical control 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  $p \leq .0001$ ). Based on the results and any possible interaction effects, the best subset of predictors were retained in the final model and subjected to further testing.

The final predictive model developed from regression modelling underwent testing through model validation and model adequacy statistical techniques. Model validation is a critical process associated with testing model applicability, or whether it can reliably predict outcomes across different samples and contexts. The appropriate validation procedure selected for this study was bootstrapping. Bootstrapping replicates the process of sample generation from an underlying population by drawing multiple samples from the original dataset. For this study, the final model was tested against 5000 replications of the sample drawn from the original dataset with replacement.

Model adequacy was also tested by examining Receiver Operating Characteristic (ROC) area under the curve (AUC) statistics, in terms of absolute performance and in comparison to available LSI-R data for the sample.

# RESULTS

A series of logistic regression models were fitted to determine the optimal set of predictors for the outcome variable of return to custody under a new sentence within two years. Results of the final model are summarised in Table 1.

The final regression model indicated that after adjusting for other predictors in the model, likelihood of return to custody was significantly associated with younger age; Indigenous cultural background; a more intensive criminal history (Copas rate and number of previous non-custodial offences); and less time in the community between the index custodial episode and the most recent previous custodial episode. Offenders serving a sentence for violent offences or robbery/theft; those who were in custody for reasons other than breach of parole; and offenders who were eligible for release to parole also had significantly higher risk of recidivism.

#### Model adequacy

The final logistic regression model was used to develop a single value estimating the probability of an offender returning to custody under a new sentence within 2 years of release. Probability estimates ranged between 0 (0% predicted probability of returning) to 1 (100% predicted probability of returning). This probability estimate comprised the value for the raw score of the Custody TRAS.

Ranges of predicted probabilities were also categorised into five partition groups indicating an increasing likelihood of return to custody (1 = .00-.19; 2 = .20-.39; 3 = .40-.59; 4 = .60-.79; 5 = .80-.99). Table 2 shows the observed rate of return to

custody outcomes for each of the five categories of the Custody TRAS.

Adequacy of the final model was first examined using the Hosmer-Lemeshow test. This test statistic did not reach statistical significance ( $\chi^2(8)$ )

= 11,195, p = .19), which indicates that there was non-significant deviation between observed and expected frequencies of return to custody within each of the five partition groups.

Table 1. Regression coefficients for the final model predicting return to custody within two years of release (N = 21,089).

Variable	B (SE)	Wald $\chi^2$	р	OR [95% CI]
Intercept	-6.474 (.292)	490.058	≤.001	
Indigenous Status				
Non-Indigenous <sup>3</sup>	1			1.00
Indigenous	.233 (.037)	39.964	≤.001	1.263 [1.175-1.358]
Age				
45+	1			1.00
Under 18	2.488 (.111)	504.86	≤.001	12.042 [9.692-14.961]
18-24	1.264 (.070)	327.99	≤.001	3.540 [3.087-4.059]
25-34	.874 (.063)	195.24	≤.001	2.398 [2.121-2.710]
35-44	.466 (.065)	51.513	≤.001	1.594 [1.404-1.811]
Index episode type				
Balance of parole only	1			
Other	.303 (.082)	13.771	≤.001	1.354 [1.154-1.589]
Most serious offence				
Other	1			
Violent	.117 (.043)	65.679	≤.001	1.417 [1.302-1.541]
Robbery / theft	.498 (.042)	138.38	≤.001	1.646 [1.515-1.788]
Number previous non-custodial	1 550 ( 142)	110 00	< 001	
sentences (log)	1.550 (.143)	116.69	≤.001	4.710 [3.556-6.240]
Copas rate	.196 (.086)	39.964	≤.001	1.217 [1.028-1.441]
Release status				
No parole	1			
Parole	.348 (.043)	65.679	≤.001	1.417 [1.302-1.541]
Most recent period of release				
No previous custody	1			
Up to one year	.895 (.066)	182.71	≤.001	2.447 [2.149-2.786]
One to three years	.314 (.065)	23.061	≤.001	1.369 [1.204-1.556]

<sup>3</sup> A beta coefficient of 1 for levels of a categorical variable indicates that this particular group served as the reference category in dummy variable calculations.

Predicted probability category	Frequency (%)	No recidivism	Recidivism		
1	8758	88.2%	11.8%		
-	(41.5%)	00.270	11.070		
2	7099	70.7%	20.20/		
	(33.7%)	70.7%	29.3%		
3	4198	F4 F0/	40 50/		
	(19.9%)	51.5%	48.5%		
4	1017		64.4%		
	(4.8%)	35.6%			
5	17	47 60/	<b></b>		
	(0.1%)	17.6%	82.4%		

Table 2. Return to custody within two years by predicted probability category (N = 21,089)

Predictive validity of the Custody TRAS model was also tested using the AUC statistic, a standard discrimination accuracy measure of for classification tools that assesses the probability that any given case with a positive outcome (in this case, an offender who returned to custody) returns a higher score than a case with a negative outcome (in this case, an offender who did not return to custody). As a rule of thumb, AUC scores greater than 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 & Lemeshow, 2000).

In the current study, the continuous raw probability score generated by the Custody TRAS yielded an AUC statistic of .75, indicating good discrimination. AUC statistics were also generated for the five category partition solution for the Custody TRAS, yielding a similarly satisfactory value of .72.

As a source of comparison, model discrimination statistics were also examined for offenders in the

study sample who had a valid LSI-R. Around four in five (81.1%; n = 17,098) offenders had a current and valid LSI-R assessment attached to their index custodial episode. Categorisation of offenders according to the five risk levels of the LSI-R returned an AUC statistic of .69 for return to custody under a new sentence within two years. This outcome indicated discrimination that was within acceptable ranges, although was slightly lower compared to the Custody TRAS<sup>4</sup>.

#### **Model Validation**

Model validation processes were applied to assess the reliability and stability of the model. Validation involves checking the model against independent samples data and determines if the results are replicable and can be generalised. In the present study, the bootstrapping method was chosen as an appropriate validation technique (for further discussion of validation methods see Raudino et al., 2018).

Using the bootstrapping process, 5000 simulated samples of the same size as the study sample were generated, by randomly selecting offenders with replacement from the original dataset. The final predictive model developed from previous regression modelling was then fitted to each of the 5000 samples. The results of bootstrapping, including average regression coefficients and empirical distributions of those coefficients across the 5000 replications are reported in Table 3.

Comparisons of regression coefficients between the original study sample and the bootstrapped replications indicate that the prediction equation showed similar performance, or was generalisable, across multiple samples. In general, coefficients for the final model and the results of bootstrapping

<sup>&</sup>lt;sup>4</sup> The presented AUC statistics for the Custody TRAS and LSI-R may not be directly comparable because they were derived from different samples; while a Custody TRAS score was estimated for all offenders in the sample, a subset of 81.1% of offenders had a valid LSI-R. To address this we replicated AUC analyses for only those offenders who had a valid LSI-R, which generated almost identical results (Custody TRAS category AUC = .724).

showed a high degree of correspondence for most predictors. It is noted that while regression coefficients were also similar across models for the Copas rate and presence of violent most serious offences, these predictors showed weaker significance values in the bootstrapped model. The negligible difference between the performance of the final model with the study sample and bootstrapped replication samples suggests a high degree of replicability or stability across samples.

Table 3. Comparison between coefficient estimates for the predictive model and averaged B, SE and empirical upper and lower bounds of 95% confidence intervals for the bootstrapped regression model.

	Predictive model				Bootstrapped model			
Variable	Coefficient		95% CI		Coefficient		95% CI	
	B (SE)	р	Lower	Upper	B (SE)	р	Lower	Upper
Indigenous status								
Non-Indigenous	1							
Indigenous	.23 (.04)	≤.001	1.18	1.36	.23 (.04)	≤.001	1.18	1.36
Age								
45+	1							
Under 18	2.49 (.11)	≤.001	9.69	14.96	2.49 (.11)	≤.001	9.68	14.94
18-24	1.26 (.07)	≤.001	3.09	4.06	1.26 (.07)	≤.001	3.11	4.06
25-34	.87 (.06)	≤.001	2.12	2.71	.87 (.06)	≤.001	2.13	2.72
35-44	.47 (.06)	≤.001	1.40	1.81	.47 (.06)	≤.001	1.41	1.82
Current sentence type								
Balance of parole only	1							
Other	.30 (.08)	≤.001	1.15	1.59	.30 (.08)	≤.001	1.15	1.60
Most serious offence								
Other	1							
Violent	.12 (.04)	≤.001	1.30	1.54	.12 (.04)	.007	1.03	1.22
Robbery / theft	.49 (.04)	≤.001	1.52	1.79	.49 (.04)	≤.001	1.51	1.79
Number previous non-custodial		4.004	2.50	6.24			2 5 0	6.40
sentences (log)	1.55 (.14)	≤.001	3.56	6.24	1.55 (.14)	≤.001	3.58	6.18
Copas rate	.19 (.09)	≤.001	1.03	1.44	.19 (.09)	.021	1.03	1.44
Release status								
No parole	1							
Parole	.35 (.04)	≤.001	1.30	1.54	.35 (.04)	≤.001	1.30	1.54
Most recent period of release								
No previous custody	1							
Up to one year	.89 (.07)	≤.001	2.15	2.79	.89 (.07)	≤.001	2.15	2.80
One to three years	.31 (.07)	≤.001	1.20	1.56	.31 (.07)	≤.001	1.20	1.55

# Development and applicability of cut-off thresholds

In order to assist decision making about screening or prioritisation of offenders, it can be valuable for tools such as the Custody TRAS to have a single calibrated cut-off score or criterion for that decision. Selection of a cut-off threshold entails a compromise between sensitivity (correctly detecting a positive outcome such as recidivism) and specificity (correctly detecting a negative outcome such as absence of recidivism).

This compromise can be optimised to some degree by statistical analysis of potential thresholds. However, it is noted that thresholds also have operational implications that require consideration at the policy level. For example, calibration with a lenient bias or focus on sensitivity may increase the likelihood of false positives (e.g. assigning offenders to limited assessment or case management resources who ultimately do not reoffend). On the other hand, calibration with a conservative bias or focus on specificity may increase false rejections (e.g. failing to provide assessment or case management resources to offenders who go on to reoffend).

Following validation of the Custody TRAS, we tested a series of hypothetical thresholds to determine an optimal calibration of sensitivity and specificity from a statistical standpoint. Table 4 shows discrimination accuracy statistics for a selection of three potential cut-off thresholds.

The positive likelihood ratio (+LR) measures the extent to which a positive predicted outcome (score above the cut-off) increases the likelihood of an offender returning to custody, whereas the negative likelihood ratio (-LR) measures the extent to which a negative predicted outcome (score below the cut-off) decreases the likelihood of an offender not returning to custody. The diagnostic odds ratio is an effectiveness measure, defined as the ratio of true positives and false positives, where higher scores indicate better performance. The sensitivity index (d') is also a signal detection measure of model performance, where scores closer to one indicate increasing correspondence between predicted positive values and observed positive values. The C-statistic is a measure of criterion bias, where scores close to zero indicate balance between sensitivity and specificity, while higher negative scores indicate greater leniency bias and higher positive scores indicate greater conservative bias.

From Table 4 it can be seen that as the cut-off threshold increases specificity also increases, while sensitivity decreases. For example, a threshold of .40 would allow for high proportions of nonrecidivists to be excluded from further case management; however sensitivity for recidivists would be low and a large proportion would also be excluded from case management. When considered in conjunction, signal detection statistics for this threshold indicated poor overall performance.

Table 4. Sensitivity	and specificity	v statistics for a set	election of tested	cut-off points.
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Cut-off	Sensitivity	Specificity	Positive	Negative	Diagnostic	ď	С
Point			Likelihood	Likelihood	Odds ratio		
			Ratio	Ratio			
.15	.90	.38	1.50	0.26	5.53	0.97	079
.20	.82	.51	1.67	0.35	4.73	0.94	-0.44
.40	.46	.83	2.88	0.64	4.47	0.89	0.55

On the other hand, the cut-off of .15 has relatively robust diagnostic accuracy although is also highly inclusive or tending towards leniency bias, as indicated by the pronounced negative C-statistic. Under these conditions most recidivists would meet the threshold although a substantial proportion of non-recidivists would also meet the thresholds<sup>5</sup>.

On the balance of further testing scenarios, we concluded that the threshold of .20 has utility as a clearly defined cut-off point that shows similar prioritisation for detecting and intervening with likely recidivists as reflected in current CSNSW policy. While this threshold tends towards leniency bias it provides a greater balance of sensitivity and specificity compared to other options (e.g. a threshold of .15) while retaining comparable discrimination accuracy.

To illustrate the potential value of the Custody TRAS threshold in determining allocation of limited case management resources, we explored a hypothetical scenario where offenders in the study sample only received a LSI-R if they first had a Custody TRAS score of .20 or higher. As previously mentioned, offenders in the sample were not all assessed with the LSI-R and 18.9% did not have a current assessment attached to their episode. Of those offenders who did not have a valid LSI-R, 23.2% returned to custody under a new sentence within two years of release. Of the offenders with an LSI-R, 28.6% were observed to return to custody.

Applying a Custody TRAS threshold of .20 for assessment with the LSI-R would result in 12,331 offenders from the total sample receiving an assessment, which is substantially lower than the 17,098 who actually were assessed. Of those offenders who would receive follow-up assessment under this scenario, 38.8% were observed to return to custody with a new sentence within 2 years. By comparison, 11.8% of offenders who received a Custody TRAS score under .20 returned to custody within two years.

# DISCUSSION

In the context of a growing prison population, in conjunction with increasing focus on implementation of evidence-based interventions to address offenders' risk of recidivism, there is a need for efficient decision making and allocation of limited resources for offender case management in custody. To this end, the present study describes the development of the Custody TRAS, an actuarial risk prediction tool for quickly and accurately assessing custody-based offenders' probability of return to custody with a new sentence within two years.

The results of this study were consistent with existing evidence that static variables relating to an offender's demographics and criminal history can be used as robust predictors of recidivism risk (May et al., 2008; Raudino et al., 2018; Smith & Jones, 2008; Xie et al., 2018). Variables that were found to significantly predict risk among NSW inmates, and were retained in the final Custody TRAS model, included age; the presence of most serious offences involving violence, robbery or theft; a history of previous offences that attracted non-custodial penalties; density of custodial episodes as indicated by the modified Copas rate (Copas & Marshall, 1998); and the recency of previous imprisonment. As with other studies of the NSW offender population (e.g. Raudino et al., 2018; Xie et al., 2018), Indigenous status was also identified as a significant predictor of recidivism; however it should be noted that this and other static variables act as statistical proxies for variance across individuals and outcomes, and does not provide meaningful information about cultural the causal relationship between background and criminal justice outcomes.

<sup>&</sup>lt;sup>5</sup> For comparison, the current CSNSW practice of prioritising offenders for various interventions according to LSI-R cut-off thresholds (medium or higher category of risk) was found to have sensitivity = .92 and specificity = .33 for those assessed inmates in the study sample.

The predictive model underlying the Custody TRAS yielded similar outcomes to research by Xie et al. (2018) in developing the CRES tool with an earlier cohort of NSW inmates released between 2008 and 2010. The CRES tool did appear to have slightly higher discrimination accuracy (AUC = .79) compared to the Custody TRAS. This may be related to the more inclusive outcome definition of any return to custody within two years (including without reconviction for new offences) used in development of the CRES model and resultant higher rates of recidivism. An additional implication is that return to custody for reasons unrelated to reoffending (e.g. breach of parole) is closely aligned in terms of predictive factors and individual characteristics to return to custody for reoffending, and may account for unexpected variance in outcomes where higher risk individuals are not observed to reoffend within a given timeframe.

Notwithstanding these considerations, the Custody TRAS is recommended as a more robust risk assessment measure by delivering comparable predictive validity to the CRES tool while addressing methodological limitations of the previous model. As previously mentioned, the CRES tool did not undergo extensive validation checks to ensure stability across inmate cohorts. There are indications that risk, age and other characteristics of the NSW inmate population are changing over time in conjunction with population growth (e.g. Howard & Corben, 2018; 2019; Stavrou, 2017), which suggests that calibration of assessment tools for optimal reliability and periodic testing and updating of tools across cohorts is beneficial in the context. In addition, the CRES tool tested outcomes at the episode level as opposed to the individual level, which may have affected distributions of error in the predictive model and violated assumptions about independence of observations.

While the discrimination accuracy of the Custody TRAS is within relatively moderate ranges from a

statistical standpoint (e.g. Hosmer & Lemeshow, 2000), results may be approaching optimal performance for actuarial assessment of offender risk. Raynor and colleagues (2000) proposed that the percentage of offenders who are correctly classified as recidivists or non-recidivists may not be expected to exceed 75% if the observed reconviction rate was 50%. The Custody TRAS also showed superior discrimination to total risk scores on the LSI-R, which were similarly developed against the criterion of return to custody (Andrews & Bonta, 1995). From an operational perspective, the model may therefore be viable both as a means of triaging offenders to further assessment with the LSI-R, and as an alternative primary assessment tool where the sole consideration is recidivism risk.

In the event that the Custody TRAS has applications in screening offenders for further intervention, results of this study indicated that a cut-off threshold of .20 delivered a relatively robust balance between sensitivity and specificity. While this threshold tended towards leniency bias, the extent of bias was moderate compared to the current criterion of medium or higher risk on the LSI-R that is routinely used by CSNSW to prioritise offenders. It may also be argued that inclusiveness in delivering case management to offenders is better aligned with priorities to reduce reoffending at the population level. However, we acknowledge that optimal calibration for operational purposes requires consideration of multiple other factors, including available resources for intervention, as well as decision making around what probability of return to custody constitutes 'high' risk and how this corresponds with delivery of interventions in accordance with the risk principle (Andrews & Bonta, 2010).

Some other limitations of the study are noted. The Custody TRAS was developed to assess risk of general recidivism in terms of return to custody, and may not be expected to have similar predictive accuracy for other outcomes such as any reoffending or specific categories of reoffending. Similarly, because the Custody TRAS was designed to predict reoffending that attracts a specific criminal justice sanction (return to custody), it may be sensitive to local trends in sentencing that affect the likelihood an offence will result in a custodial or a non-custodial penalty. In addition, the Custody TRAS generates information about probability of recidivism only and is not intended to be used as a proxy indicator of the presence or absence of specific domains of criminogenic need. As a result the model would have optimal utility as a triaging tool for comprehensive assessment of dynamic risk factors or when used in conjunction with other measures of needs.

While it is important to highlight the parameters and limited conditions under which such tools are applied, the results of this study nevertheless demonstrate that the Custody TRAS is a viable method for quickly and accurately assessing risk of recidivism among custody-based offenders. The model applies standardised static variables that are readily available in the CSNSW operational database, and therefore can be linked to existing data streams to generate almost instantaneous estimates of risk for large numbers of offenders. As indicated by the results, this method has the capacity to both achieve efficiency benefits relative to clinician-scored measures such as the LSI-R, and also potentially improve consistency and accuracy in risk assessment at the population level. Under correctional contexts where limited case management resources are applied to steadily increasing inmate populations, the efficiency dividends afforded by tools such as the Custody TRAS may facilitate reallocation of staff time and expertise to processes of intervening with offenders so as to reduce their risk of reoffending and reimprisonment.

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Corrections Research, Evaluation & Statistics Governance & Continuous Improvement Corrective Services NSW GPO Box 31 Sydney NSW Australia

Telephone: (02) 8346 1556 Email: research.enquiries@justice.nsw.gov.au