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Predictive validity of risk/needs assessment for young offenders under community supervision

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Aims: *To assess whether Youth Level of Service/Case Management Inventory Australian Adaptation (YLS/CMI-AA) risk/needs data improve recidivism prediction for young offenders under community supervision, compared to static risk data from the Bureau's Reoffending Database (ROD).*

Method: *The analysis included all 1,050 young offenders who commenced a supervised community order (other than bail or parole) in 2014 with a valid YLS/CMI-AA and ROD record. Recidivism was defined as a new proven offence within 12 months of order commencement. Logistic regression assessed the individual and collective relationships of static risk factors and YLS/CMI-AA scores to recidivism. Area Under the Curve (AUC), model fit indices and multiple cross-validation methods were used to evaluate the models.*

Results: *Interactions between variables in models built with the full sample necessitated that separate models be built for Indigenous and non-Indigenous offenders. For non-Indigenous offenders, the AUC for the combined (ROD with YLS/CMI-AA) model (.767, 95% CI (.728, .807)) was within the acceptable range (0.7-0.8) but did not significantly outperform the ROD-only model (.740, (95% CI .698, .781)). For Indigenous offenders, AUCs were significantly lower than for non-Indigenous offenders, below the acceptable range, and also showed no significant benefit from combining YLS/CMI-AA and ROD data. Compared with AUCs for the combined model, cross-validated AUCs were lower, and corresponding AUCs for the 2013 cohort were inconsistent.*

Conclusion: *YLS/CMI-AA data did not significantly improve the predictive accuracy of static risk-based models of recidivism for Indigenous or non-Indigenous offenders. Validation methods suggested that the results may not generalise beyond the current cohort.*

INTRODUCTION

Recidivism is the norm, rather than the exception for juvenile offenders who reach the court system. Payne and Weatherburn (2015) reported 10-year reconviction rates of 68 per cent for juveniles first convicted in court in 1999; they typically reoffended quickly and, in many cases, repeatedly. The attendant costs to offenders, the criminal justice system and the community are substantial. Risk assessment has a number of important functions for criminal justice agencies, including prediction and classification (to estimate the volume of recidivists and their offending and to match service intensity to recidivism risk levels), and identifying predictors that may serve as targets for intervention. These two functions of risk assessment are very different (Caudy, Durso, & Taxman, 2013) and yet closely related and complementary. Actuarial models constructed from administrative data (e.g. Smith, 2010) may be used to predict recidivism risk, classify risk levels, and identify unmodifiable or 'static' risk factors (such as criminal history). Modern risk/needs inventories may also predict and classify but such tools give primacy to the assessment of modifiable or 'dynamic' risk factors (such as peer relations) that may be targeted to reduce recidivism risk. Legislation and supervision policies place special emphasis on addressing the needs of juvenile offenders (Department of Justice, 2014; McGrath & Thompson, 2012). The current study explores the benefits of combining these approaches.

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ASSESSMENT OF STATIC AND DYNAMIC RISK

Locally-constructed actuarial risk assessments are useful where brevity and efficiency are essential (Schwalbe, 2007). Such assessments have been developed and widely applied for juveniles, adults and more specific offender populations in NSW and elsewhere (e.g. Fitzgerald & Graham, 2016; Krysik & LeCroy, 2002; Smith, 2010; Stavrou & Poynton, 2016). These assessments typically draw from administrative criminal justice data limited to static risk factors (including offence history and socio-demographic characteristics such as ethnicity). Scholars disagree on whether static risk factors are true influences on offending (Lofthouse et al., 2014) or merely markers of true influences (Lloyd, 2015).[1] This may reflect the fact that such factors consistently predict recidivism but are unmodifiable (Payne & Weatherburn, 2015; Ringland, 2011; Smith, 2010; Stavrou & Poynton, 2016). Static risk-based assessment instruments can inform decisions about supervision intensity supporting the 'risk' principle of the dominant risk-need-responsivity framework (RNR; Andrews & Bonta, 2007). The risk principle seeks to '[match] levels of treatment services to the risk level of the offender' (Andrews & Bonta, 2007: 279), rather than to make predictions about individuals. For example, 'high' risk offenders should receive a higher level of service (e.g. more regular supervision) than 'low' or 'medium' risk offenders. Static risk-based assessments cannot inform case planning or risk reduction.

Within RNR, the need principle requires that services target specific criminogenic needs: modifiable factors that are particularly relevant to an individual's offending and, when addressed, that reduce their risk of offending (Vincent, 2015). Decisions about treatment matching therefore rely on information about the relevance of specific dynamic risk factors. Modern risk assessment inventories, such as the Youth Level of Service/Case Management Inventory (YLS/CMI; Hoge, 2005), are predominantly focused on identifying these needs and do so using an extensive list of dynamic factors that have been theoretically and statistically linked with recidivism (Caudy et al., 2013; McGrath & Thompson, 2012). For their more comprehensive (but not exhaustive; see Ward, 2016) approach, these tools are generally referred to as risk/needs assessment instruments. Dynamic risk factors are less consistent predictors of recidivism than static risk factors, particularly when the effects of static risk factors are taken into account (Caudy et al., 2013; Ringland, 2011).[2]

Stavrou and Poynton (2016) suggest that administrative data are largely sufficient for developing screening models. Such models could be used to identify the subgroups for whom further assessment would be most warranted. This approach would also allow a more thorough process of needs assessment if the initial static risk-based assessment were to identify only a subset of offenders for further assessment/intervention. They also note a resurgence of interest among criminal justice agencies in risk assessment tools built solely with static risk factors, due to their relative ease of use, efficiency and cost-effectiveness, compared with more recent tools that include dynamic factors. Recidivism risk models must balance the increased accuracy gained through the inclusion of dynamic factors against the costs of data collection (Ringland, Weatherburn, & Poynton, 2015). If risk/needs assessment data are readily available, including these in actuarial predictive models could improve the predictive accuracy of recidivism risk at little cost, in turn supporting service demand estimation and efficient resource allocation to those at greatest risk of recidivism. This approach can also clarify the independent contribution of specific dynamic risk factors to recidivism. Knowledge of the relative significance of specific dynamic factors would aid service planning by identifying intervention targets and help in selecting appropriate evidenced-based interventions (Washington State Institute for Public Policy, 2015) that can address criminogenic needs to reduce recidivism risk.

THE YOUTH LEVEL OF SERVICE/CASE MANAGEMENT INVENTORY

The Australian Adaptation of the Youth Level of Service/Case Management Inventory (YLS/CMI-AA; Hoge & Andrews, 1995) combines a standardised actuarial risk/needs assessment tool containing static and dynamic risk factors, measures of responsivity, and a case planning function. The actuarial tool contains 47 items and has been normed on several offender populations including juveniles in NSW. The items produce a total risk/needs score that can be classified as either low, moderate, moderate-high, or high. In NSW, these categories correspond to the following suggested levels of service: no contacts (conclude supervision), two, four, and six contacts per month, although clinical judgement and other assessments can be brought to bear when setting the final level of service (Department of Justice, 2014). The YLS/CMI-AA is a core element of case management plans that seek to reduce criminogenic needs and is administered to all young offenders in NSW issued with a supervised order. By policy, it is completed within six weeks of order commencement and on a six-monthly basis thereafter unless supervision has been discontinued. Reassessments may occur sooner than six months if a young person reoffends or circumstances relevant to supervision are thought to have changed significantly.

The YLS/CMI-AA also provides subscales scores aligning with each of the eight 'criminogenic need' domains set out by the RNR framework. The 'big four' domains (referred to in this Bulletin as *Offences, Peers, Personality,* and *Attitudes*) contain the risk factors that are thought to be most directly linked to recidivism and that RNR suggests should be the primary targets of correctional programming (Caudy et al., 2013). The 'moderate four' domains are referred to here as *Family, Education, Leisure* and *Drugs. Offences* is the only subscale containing measures of static risk. Each subscale score can be classified as low, medium, or high; medium and high scores are populated into individualised intervention plans for further consideration (Department of Justice, 2014). Thus, the YLS/CMI-AA supports RNR's case classification principles including risk (treatment intensity should increase with recidivism risk level) and need (treatment type should be matched to individual criminogenic needs; Hoge, 2005).[3]

If YLS/CMI-AA data can be shown to improve static risk-based recidivism models, this might support their routine inclusion in future recidivism models. Relevant agencies might also explore whether YLS/CMI-AA data could be used to improve models predicting recidivism with other cohorts (e.g. pre-sentenced offenders, offenders on unsupervised orders). Such expansion, however, must be balanced against the attendant administration costs (labour, training, licencing, etc.) and demands on young people and YLS/CMI-AA informants (families, schools, etc.). It may also be important to consider the potential for differences in predictive validity between gender and ethnic subgroups. Thompson and McGrath (2012) pointed out that variation in the type and confluence of risk factors between subgroups may be masked by aggregated analyses, and that factors such as ethnicity may affect the likelihood and nature of their interactions with the criminal justice system. These authors stressed the need for research reporting subgroup differences on the YLS/CMI-AA and its relationship with recidivism.

PRIOR STUDIES

Previous static risk-based studies of recidivism by community-based juvenile offenders have shown an acceptable level of predictive accuracy as indicated by AUC values between 0.7 and 0.8 (Hosmer & Lemeshow, 2000); for example, Smith and Jones (2008) reported an AUC of .758, 95% CI (.743, .774) for two year recidivism. These and other similar models by BOCSAR have been used to forecast the volume of offenders whose predicted risk of recidivism exceeds a particular threshold (Stavrou & Poynton, 2016). Factors that commonly predict recidivism by community-based juvenile offenders include male gender, younger age, Indigenous status and multiple prior offences; multiple concurrent offences have also featured (Smith, 2010; Smith & Jones, 2008). Predictor sets vary somewhat with methodological factors, including the length of observation (longer periods increase predictive estimates, Payne & Weatherburn, 2015), sampling (e.g. including unsupervised or less serious offenders, Lind, 2011), and measurement (e.g. excluding cautions from counts of prior finalisations, Smith, 2010). Models should be appropriate to a specific cohort and need to respecified and recalibrated over time (Stavrou & Poynton, 2016).

Non-administrative data have also been interrogated to identify factors that may increase the accuracy of predictive models or provide insights for case planning and risk reduction. Using data extracted from the files of 392 juvenile offenders, Weatherburn, Cush, and Saunders (2007) identified numerous bivariate predictors of recidivism, of which two (school attendance and school suspension/expulsion) predicted recidivism independent of criminal history. Among offenders with few criminal justice contacts, Ringland et al. (2015) found various child protection indicators that predicted recidivism independent of common static risk factors, but the apparent contribution of the child protection indicators was small. YLS/CMI-AA data has two clear advantages over these data: it is held by Juvenile Justice (and can therefore be more readily linked to criminal record data), and it intentionally contains a wide array of dynamic factors that are pertinent to recidivism.

Previous studies suggest that the YLS/CMI total risk/needs score has moderate predictive validity, or correspondence, with general recidivism. Olver, Stockdale, and Wormith's (2014) meta-analysis reported a fixed effect size of .25, 95% CI (.24, .27) drawing on 30 studies. Schwalbe (2007) calculated a weighted AUC (Area Under the Receiver Operating Characteristic Curve) of .641, 95% CI (.506, .777) over 11 studies and reported that cross-validated AUCs (CV-AUCs) were significantly lower than the native (i.e. full sample) AUCs. Cross-validation averages the AUC for multiple subsamples to more realistically estimate how well a model generalises to new cases (Luque Fernandez, Maringe, & Nelson, 2017). Very few estimates in these meta-analyses were derived from Australian samples, however. This is problematic, given robust evidence of jurisdictional variation in the predictive validity of the Level of Service tools (Andrews et al., 2011); such variation might indicate problems with generalisability or with implementation.

McGrath and Thompson (2012) reported an AUC of .652, 95% CI (.634, .670) for a large sample of community-based juvenile offenders in NSW (N=3,568); a CV-AUC was not reported. These results fall below the acceptable level for AUC and indicate a 'small' effect size (0.1-0.3; Cohen, 1988), consistent with the meta-analyses discussed above. However, predictive validity estimates may be attenuated given that youth with high scores should (in theory) receive effective and intensive interventions which will reduce their recidivism risk. Attainable levels of accuracy may also be limited by unmeasured heterogeneity among offenders (Hess & Turner, 2017). Few studies, for example, measure situational predictors, contextual predictors (such as concentrated disadvantage) or their interaction with individual level predictors (Baglivio, Wolff, Jackowski, & Greenwald, 2017; Wikström, Ceccato, Hardie, & Treiber, 2010). It should also be acknowledged that modest predictive validity indices do not preclude the instrument from being used to effectively place offenders into groups with meaningfully different rates of recidivism.

Australian studies have not yet examined whether YLS/CMI-AA data improve the predictive performance of recidivism models built with criminal history data. The study by McGrath and Thompson (2012) found that recidivism by young offenders could be best predicted with a combination of the YLS/CMI-AA *Offences* subscale and four of its dynamic subscales (*Education*, *Peers*, *Drugs*, and *Attitudes*). Thompson & McGrath (2012) also found that the YLS/CMI-AA performed less well in predicting recidivism by Indigenous offenders (AUC .604, 95% CI (.569, .639)) than offenders from offenders from Australian non-Indigenous (AUC .644, 95% CI (.617, .671)) or other ethnic backgrounds (AUC .652, 95% CI (.613, .692)). These studies made an important contribution but did not control for static risk (other than the *Offences* subtotal, which is largely limited to dichotomous measures of criminal history), and the data that they analysed pertained to the first three years' use of the YLS/CMI-AA. Predictive validity estimates for risk assessment tools also need to be reviewed and recalibrated over time. YLS/CMI-AA policies and practices have evolved (Department of Justice, 2014) which may have impacted on the quality and coverage of Juvenile Justice's YLS/CMI-AA data. Updated analyses using recent YLS/CMI-AA data are in train (Andrew McGrath, personal communication, 25 May 2017).

Studies of other risk tools also offer other insights into potential importance of dynamic risk factors. The dynamic risk scales of the Structured Assessment of Violence Risk in Youth (SAVRY; Borum, Bartel, & Forth, 2006), the most well-researched alternative to the YLS/CMI-AA, have had additional predictive validity over static predictors of recidivism among US juveniles (Vincent, Guy, Gershenson, & McCabe, 2012) and have predicted recidivism among young Australian detainees (Shepherd, Luebbers, Ogloff, Fullam, & Dolan, 2014). Selected dynamic risk scales of the Level of Service Inventory – Revised (LSI-R) also improved the predictive accuracy of static-risk bask models of recidivism by adult offenders in NSW (Ringland, 2011). While this improvement was small, and the impact on model fit was not reported, Ringland (2011) observed that these dynamic risk scales could also have value for quasi-experimental program evaluations as controls for otherwise unmeasured differences between treated and untreated groups.

AIMS

In light of the material reviewed above, this study examines a large sample of juveniles under community supervision and specifically aims to:

1. Develop a model of recidivism based on static predictors.
2. Examine the relationship of the YLS/CMI-AA risk/need score and subscale scores to recidivism.
3. Test whether YLS/CMI-AA data predicts recidivism over and above static predictors.

METHOD

DATA SOURCES

The study utilised data from the Juvenile Justice Supervision Management Program and Client Information Management System and the Bureau's Reoffending Database (ROD). ROD contains records of all offences since 1994 and custodial episodes since 2000. The data drawn from Juvenile Justice included details of all supervised community orders of at least six weeks' duration between 2011 and 2015, together with all YLS/CMI-AA administrations pertaining to offenders in the dataset. The Juvenile Justice data were linked to ROD, taking the first court appearance at which a person received a supervised community order in each given year (e.g. 2014) as their index appearance for that year. For offenders with multiple YLS/CMI-AA administrations, the record pertaining to the first valid YLS/CMI-AA administration (the most recent administration in the six months prior to the appearance, or else, the first within six weeks of this appearance) was selected.

SAMPLE SELECTION

A total of 1,316 offenders in Juvenile Justice's database were linked to a valid order (i.e. excluding bail supervision and parole) with a 2014 start date in ROD. All 31 offenders with order start dates that did not align with ROD, 86 offenders without YLS/CMI-AA data, and 149 offenders with invalid YLS/CMI-AA data (i.e. collected more than six months prior to or more than six weeks after their order started) were excluded.[4] The final analysis sample contained 1,050 offenders with a valid YLS/CMI-AA: 212 females and 838 males; 508 Indigenous and 535 non-Indigenous offenders, and 7 offenders with unknown Indigenous status.

DEPENDENT VARIABLE

- **Recidivism** (caution, conference, or court appearance with a new proven offence committed up to 12 months after the index appearance and finalised by 30 June 2016, with no adjustment for time spent in custody during this period): yes or no.

INDEPENDENT VARIABLES

While a wide range of variables were considered during the development of the models, only those in the models reported or discussed in this paper are presented below. Variables were categorised (rather than treated as continuous) to facilitate comparisons with prior studies (e.g. Smith & Jones, 2008).

Demographic, index appearance and criminal history variables from ROD

- **Gender**: male or female.
- **Indigenous status** (ever identified as Aboriginal or Torres Strait Islander): yes or no/unknown.
- **Aged under 13 at first finalisation:** (caution/conference/appearance with proven charge/s): yes or no.
- **Age at the index appearance** (in years): under 15, 15, 16, 17 and over.
- **Concurrent offences** (proven at the index appearance): 0, 1, multiple.
- **Prior finalisations** (caution/conference/court appearance with proven charge/s) in the five years prior to the index appearance: 0, 1, 2, 3, 4-5, 6 and over.[5]
- **Prior custody** (remand, prison or custodial sentence of at least one day's duration): yes or no.
- **High socioeconomic disadvantage** (residential postcode at the index appearance within the most disadvantaged SEIFA quintile; Australian Bureau of Statistics, 2011): yes or no.

YLS/CMI-AA data from Juvenile Justice database

Data from administrations of the Youth Level of Service/Case Management Inventory – Australian Adaptation (YLS/CMI-AA):

- **Date of YLS/CMI-AA completion**
- **Total risk/needs score**
- **Total risk/needs rating**: low (0-7), medium (8-17), medium-high (18-30), high (31 to 48)
- **Subscale scores for all eight domains**
  - Prior and current offences: (*Offences*)
  - Family and living circumstances (*Family*)
  - Education and employment (*Education*)
  - Peer relations (*Peers*)
  - Substance abuse (*Drugs*)
  - Leisure and recreation (*Leisure*)
  - Personality and behaviour (*Personality*)
  - Attitudes and orientation (*Attitudes*)
- **Subscale ratings for all eight domains** (low, medium, high; cutoffs varied by domain)
  - Subscales with a non-linear relationship with recidivism are input as a categorical or dichotomous independent variable (rather than as a continuous variable), per Ringland (2011).

YLS/CMI-AA data were also extracted on the three major strengths items (individual, family, and community) and the professional override flag (which indicates whether the calculated risk/needs level was manually adjusted in consultation with management). Comprehensive analyses of these data were beyond the scope of this study, but would appear warranted, given emerging findings showing that override reduces predictive validity (Schmidt, Sinclair, & Thomasdóttir, 2016).[6]

ANALYSIS

All analyses were undertaken in Stata 13.1 (StataCorp, 2013). Binary logistic regression was used to identify bivariate associations between each potential independent variable and recidivism. The multivariate models were built in three stages using multivariate logistic regression. At each stage, stepwise regression was used to adjust the terms in the model (permitting terms to be entered at $p<.05$ and removed at $p=.05$). Differences at each step were evaluated using the Area Under the Receiver Operating Characteristic Curve statistic (AUC). The AUC represents the probability that a person who reoffends (during the study period) will have a higher predicted probability of recidivism than a person who does not reoffend. Scores ranges from 0.5 to 1.0, with higher scores indicating a better fitting model and scores of 0.7 to 0.8 considered 'acceptable' (Hosmer & Lemeshow, 2000).

The first stage of the analysis was restricted to the possible static risk factors extracted from ROD. Variables that were significantly related to recidivism ($p<.05$) at the bivariate level were tested using the methods described above. Other variables that have been found to predict recidivism in previously validated models or which may have intrinsic interest to policy makers were tested using manual methods. Preliminary analyses of the full sample (N=1,050) identified strong interactions ($p<.01$) between Indigenous status and other variables including prior offending, so the final analyses were undertaken separately for Indigenous and non-Indigenous offenders.[7] The second stage sought to identify the combination of YLS/CMI-AA total or subscale scores that resulted in the best fitting model using only these data. The third stage used both ROD and YLS/CMI-AA data.

Model efficiency was assessed using the AIC and BIC; smaller values indicate that a model fits the data more efficiently (Williams, 2013). Models were tested using alternative model-building strategies (forward selection, backwards elimination, hierarchical regression forcing terms into the model). The Nagelkerke pseudo r-square is reported as a relative measure of which model best predicts recidivism. This measure is sometimes taken as an objective measure of the model's ability to predict recidivism (ranging from 0 to 1). The Hosmer-Lemeshow goodness of fit statistic tests whether the model functions differently at different probabilities of recidivism; a *p*-value below .05 indicates significant variation.

External validity was assessed by using *k*-fold cross-validation to estimate the average AUC for *k* mutually exclusive 'test' samples, using estimates derived from the remaining cases

Table 1. Descriptive statistics and bivariate relationships with recidivism for ROD data

		Non-Indigenous				Indigenous			
		n (%)	% Re-offend	Odds Ratio (95% Confidence Interval)	*p*	n (%)	% Re-offend	Odds Ratio (95% Confidence Interval)	*p*
Age at index appearance	>=17 years	193 (35.6)	46.1	1.00	[a]	139 (27.4)	59.0	1.00	**
	16 years	157 (29.0)	52.9	1.31 (0.86, 2.00)	.209	123 (24.2)	67.5	1.44 (0.87, 2.40)	.156
	15 years	111 (20.5)	50.5	1.19 (0.75, 1.90)	.466	103 (20.3)	74.8	2.06 (1.18, 3.60)	.011
	<15 years	81 (14.9)	63.0	1.99 (1.17, 3.38)	.012	143 (28.2)	76.9	2.32 (1.38, 3.88)	.001
Age at first finalisation	>=13 years	482 (88.9)	48.1	1.00	***	306 (60.2)	64.7	1.00	**
	<13 years	60 (11.1)	78.3	3.90 (2.05, 7.34)	<.001	202 (39.8)	76.2	1.75 (1.17, 2.61)	.006
Concurrent offences	0-1	278 (51.3)	41.4	1.00	***	181 (35.6)	62.4	1.00	*
	>1	264 (48.7)	62.1	2.32 (1.65, 3.28)	<.001	327 (64.4)	73.1	1.63 (1.11, 2.41)	.013
Prior finalisations	0	135 (24.9)	27.4	1.00	***	39 (7.7)	64.1	1.00	[b]
	1	98 (18.1)	41.8	1.91 (1.10, 3.31)	.022	65 (12.8)	69.2	1.26 (0.54, 2.92)	.590
	2	84 (15.5)	60.7	4.09 (2.30, 7.30)	<.001	70 (13.8)	60.0	0.84 (0.37, 1.89)	.673
	3	68 (12.6)	67.7	5.54 (2.93, 10.43)	<.001	82 (16.1)	73.2	1.53 (0.68, 3.46)	.309
	4-5	76 (14.0)	59.2	3.84 (2.12, 6.96)	<.001	112 (22.1)	69.6	1.28 (0.90, 2.77)	.523
	>5	81 (14.9)	72.8	7.10 (3.83, 13.19)	<.001	140 (27.6)	72.9	1.50 (0.71, 3.19)	.289
Prior custody	No	291 (53.7)	40.6	1.00	***	186 (36.6)	65.1	1.00	
	Yes	254 (46.3)	64.1	2.62 (1.85, 3.72)	<.001	322 (63.4)	71.7	1.36 (0.93, 2.01)	.116
Disadvantage	Other	406 (74.9)	48.8	1.00	*	369 (72.6)	68.0	1.00	
	Highest	136 (25.1)	59.6	1.55 (1.04, 2.29)	.030	139 (27.4)	72.7	1.25 (0.81, 1.93)	.313
Total		542 (100)	51.5			508 (100)	69.3		

Note. Overall likelihood ratio chi-square test: *$p<.05$, **$p<.01$, ***$p<.001$.
a. Overall likelihood ratio chi-square test $p=.087$; $p=.008$ for a continuous term for age (odds ratio 0.84, 95% CI (0.73, 0.96).
b. Overall likelihood ratio chi-square test $p.=.453$; $p=.075$ for a continuous term for priors (odds ratio 1.06, 95% CI (0.99, 1.13).

Table 2. Descriptive statistics and bivariate relationships with recidivism for YLS/CMI-AA data

		Non-Indigenous				Indigenous			
		Mean	Range	Odds Ratio (95% Confidence Interval)	*p*	Mean	Range	Odds Ratio (95% Confidence Interval)	*p*
Total risk/needs score		19.1	1-45	1.09 (1.07, 1.12)	<.001	21.3	2-45	1.05 (1.03, 1.08)	<.001
Original subscale scores									
Offences		3.4	0-9	1.41 (1.27, 1.56)	<.001	4.3	0-9	1.11 (1.01, 1.23)	.032
Family		2.5	0-7	1.38 (1.24, 1.53)	<.001	2.8	0-7	1.18 (1.05, 1.33)	.006
Education		2.7	0-7	1.30 (1.19, 1.42)	<.001	3.2	0-7	1.19 (1.07, 1.32)	.001
Peers		2.2	0-4	1.54 (1.34, 1.76)	<.001	2.5	0-4	1.34 (1.14, 1.57)	<.001
Drugs		2.5	0-6	1.22 (1.11, 1.33)	<.001	2.5	0-6	1.08 (0.98, 1.20)	.123
Leisure		1.6	0-3	1.52 (1.30, 1.79)	<.001	1.7	0-3	1.28 (1.07, 1.52)	.006
Personality		2.8	0-7	1.30 (1.19, 1.42)	<.001	2.9	0-7	1.17 (1.06, 1.29)	.003
Attitudes		1.4	0-5	1.48 (1.30, 1.69)	<.001	1.5	0-5	1.30 (1.13, 1.50)	<.001
Modified subscale scores									
Family [a]		0.7	0-1	3.52 (2.40, 5.18)	<.001	0.8	0-1	2.07 (1.36, 3.16)	.001
Education [b]		1.0	0-2	1.89 (1.53, 2.34)	<.001	-			
Personality [c]		-				1.4	0-2	1.64 (1.27, 2.12)	<.001
		n (%)	% Re-offend	Odds Ratio (95% Confidence Interval)	*p*	n (%)	% Re-offend	Odds Ratio (95% Confidence Interval)	*p*
Risk/needs level	Low	62 (11.4)	19.4	1.00	***	19 (3.7)	42.1	1.00	***
	Medium	183 (33.8)	37.7	2.52 (1.26, 5.07)	.009	158 (31.1)	60.8	2.13 (0.81, 5.59)	.125
	Medium-High	230 (42.4)	62.6	6.98 (3.52, 13.83)	<.001	253 (49.8)	73.9	3.90 (1.50, 10.10)	.005
	High	67 (12.4)	80.6	17.31 (7.22, 41.47)	<.001	78 (15.4)	78.2	4.93 (1.71, 14.21)	.003
Timing of YLS/CMI-AA[d]	0-42d post	337 (62.2)	49.0	1.00		270 (53.2)	67.4	1.00	
	183-1d prior	205 (37.8)	55.6	1.31 (0.92, 1.85)	.133	238 (46.9)	71.4	1.21 (0.83, 1.77)	.327
Total		542 (100)	51.5			508 (100)	69.3		

Note. Overall likelihood ratio chi-square test: *$p<.05$, **$p<.01$, ***$p<.001$.
a. Dichotomous: Medium (2-3) or High (4-7), vs Low (0-1).
b. Ordinal: High (4-7) vs. Medium (2-3) vs. Low (0-1).
c. Ordinal: High (3-7) vs Medium (1-2) vs Low (0).
d. n=29 (2.7%) offenders had YLS/CMI-AA data collected on the day that their order commenced.

(Zou, Liu, Bandos, Ohno-Machado, & Rockette, 2011). Cross-validated AUC (CV-AUC) provides a more conservative and realistic estimate of 'out of sample' predictive performance than the full sample AUC (Luque-Fernandez, Maringe, & Nelson, 2017).[8] The chosen approach sought to identify the additional predictive value of risk assessment data over available static risk factors and to identify which subscales independently predicted recidivism.

RESULTS

DESCRIPTIVE AND BIVARIATE RESULTS

Table 1 presents the prevalence and bivariate relationships with recidivism (reoffending within 12 months of the index appearance) for ROD variables that predicted recidivism in the later multivariate models. For both the Indigenous and non-Indigenous subgroups, younger age at the index appearance and first finalisation, and multiple concurrent offences were associated with higher rates of recidivism ($p<.05$). Higher numbers of prior finalisations, a history of one or more days in custody, and high levels of socio-economic disadvantage were also associated with higher rates of recidivism for non-Indigenous offenders only. The overall recidivism rate was 60.1 per cent; recidivism was significantly more common for Indigenous offenders (69.3%) than for non-Indigenous offenders (51.5%; odds ratio 2.13, 95% CI (1.65, 2.74), $p<.001$) . Gender was not associated with recidivism for either subgroup (or for the full sample).

Table 2 presents descriptive statistics and bivariate relationships with recidivism for YLS/CMI-AA data. The means for the YLS/CMI-AA total and subscale scores showed significant positive relationships with recidivism for non-Indigenous offenders and, with the exception of the *Drugs* subscale, for Indigenous offenders. The risk/needs level discriminated well for non-Indigenous offenders (significant differences in recidivism rates for all adjacent risk/needs levels) but not for Indigenous offenders (no significant differences between adjacent risk/needs levels). Three subscales showed a non-linear relationship with recidivism, confirmed using a Box-Tidwell test (Menard, 2002). The *Family* subscale was dichotomised at its low range (0 to 1); medium range scores on this subscale (2 to 3) showed a similar association with recidivism to high range scores (4 to 7) for Indigenous and non-Indigenous offenders. A strong ordinal association with recidivism was apparent across the three ranges (low, medium, high) of the *Education* subscale for non-Indigenous offenders and of the *Personality* subscale for non-Indigenous offenders. The wide variation in possible values for each scale (0 to 1 for the modified *Family* subscale; 0 to 9 for the *Offences* subscale) must be considered when making within-table comparisons. YLS/CMI-AA risk/needs levels were typically in the medium or medium-high range for both Indigenous and non-Indigenous offenders and the majority of offenders did not have a valid pre-existing YLS/CMI-AA.

MULTIVARIATE RESULTS

Table 3 presents multivariate relationships with recidivism for non-Indigenous offenders for models containing ROD data (Model 1), modified YLS/CMI-AA subscale scores (Model 2), and ROD combined with modified YLS/CMI-AA subscale scores that independently predicted recidivism (Model 3; the 'combined' model). With regards to 'static' factors, younger age at first finalisation, multiple concurrent offences, prior convictions, and high disadvantage independently predicted recidivism within 12 months in Models 1 and 3; younger age at the index appearance and prior custody were also significant in Model 1. The best fitting model using only YLS/CMI-AA data (Model 2) retained the *Offences, Family, Education and Attitudes* subscales.

Table 4 presents the ROD, YLS/CMI-AA and combined models for Indigenous offenders. Younger age at the index appearance, younger age at first finalisation, and multiple concurrent offences independently predicted recidivism within 12 months in the ROD model (Model 1). The best fitting YLS/CMI-AA model retained the *Peers* and *Personality* subscales (Model 2). The combined model retained the age predictors from Model 1 and two different YLS/CMI-AA subscales: *Family* (modified) and *Attitudes*.

Alternative specifications of these models (using the YLS/CMI-AA total risk/needs score or the original YLS/CMI-AA subscale scores) resulted in AUC values that were lower, or that were the same but at the expense of efficiency (i.e. higher AIC/BIC values). Similarly, although gender was not associated with recidivism it was considered in the multivariate models because male gender has predicted recidivism in earlier static risk-based models (e.g. Smith, 2010). However, when forced into the combined model, gender did not significantly improve fit for either subgroup (adjusted odds ratios were approximately 1.3, with p-values of close to .1).

Predictive power was acceptable (AUC between 0.7 and 0.8) for all non-Indigenous models but below this range for all Indigenous models. For both the Indigenous and non-Indigenous models, the point estimates for the Model 3 AUCs fall within the AUC confidence intervals for Model 1, indicating that the inclusion of YLS/CMI-AA data does not significantly improve the prediction of recidivism over ROD data alone for either group. Model diagnostics indicated no evidence of multicollinearity in these models, with variance inflation factors below 2.5 (Allison, 2012) and most parameters varying only slightly (10-20%) between models, which suggests that any intra-model confounding is small.

Table 3. Comparison of ROD, YLS/CMI-AA, and combined recidivism models (non-Indigenous)

	1: ROD		2: YLS/CMI-AA		3: Combined		
	Odds Ratio	*p*	Odds Ratio	*p*	Odds Ratio	(95% Confidence Interval)	*p*
Age at index appearance		*	-				
>=17 years	1.00						
16 years	1.56	.067					
15 years	1.41	.192					
<15 years	2.48	.004					
Age at first finalisation			-				
>=13 years	1.00				1.00		
<13 years	2.11	.040			2.35	(1.16, 4.74)	.017
Concurrent offences			-				
0-1	1.00				1.00		
>1	1.72	.006			1.50	(1.00, 2.24)	.049
Prior finalisations		***	-				**
0	1.00				1.00		
1	1.48	.186			1.42	(0.79, 2.57)	.242
2	3.31	<.001			2.79	(1.48, 5.26)	.001
3	4.62	<.001			3.94	(1.99, 7.82)	<.001
4-5	2.51	.008			2.07	(1.05, 4.06)	.035
>5	4.35	<.001			2.60	(1.26, 5.35)	.010
Prior custody			-				
No	1.00						
Yes	1.71	.011					
Disadvantage			-				
Other	1.00				1.00		
Highest	1.69	.020			1.66	(1.06, 2.60)	.026
YLS/CMI-AA subscale scores							
Offences [a]	-		1.29	<.001	1.15	(1.02, 1.30)	.023
Family (modified) [b]	-		1.87	.005	2.05	(1.30, 3.23)	.002
Education (modified) [c]	-		1.34	.019			
Peers	-						
Drugs	-						
Leisure	-						
Personality	-						
Attitudes	-		1.20	.015	1.26	(1.08, 1.46)	.002
AUC (95% CI)	.740 (.698, .781)		.727 (.685, .769)				.767 (.728, .807)
AIC		673.3		669.8			646.1
BIC		729.1		691.3			697.6
pseudo r^2		.138		.121			.171
10-fold cross-validated AUC (95% CI; average training sample n=488)							.748 (.721, .775)

Note. - = Term was not input to the model. Overall likelihood ratio chi-square test *p<.05, **p<.01, ***p<.001
a. When Offences is removed from the combined model, Education is retained (p=.040).
b. Dichotomous: Medium/High (2-7) vs. Low (0-1).
c. Ordinal: High (4-7) vs. Medium (2-3) vs. Low (0-1).

Table 4. Comparison of ROD, YLS/CMI-AA, and combined recidivism models (Indigenous)

	1: ROD		2: YLS/CMI-AA		3: Combined		
	Odds Ratio	***p***	**Odds Ratio**	***p***	**Odds Ratio**	**(95% Confidence Interval)**	***p***
Age at index appearance		*	-				
>=17 years	1.00				1.00		
16 years	1.35	.250			1.22	(0.72, 2.05)	.461
15 years	1.98	.018			1.81	(1.02, 3.21)	.042
<15 years	1.98	.011			1.95	(1.14, 3.34)	.015
Age at first finalisation			-				
>=13 years	1.00				1.00		
<13 years	1.64	.019			1.61	(1.06, 2.45)	.026
Concurrent offences			-				
0-1	1.00						
> 1	1.64	.015					
Prior finalisations			-				
Prior custody			-				
Disadvantage			-				
YLS/CMI-AA subscale scores							
Offences	-						
Family (modified)[a]	-				1.60	(1.02, 2.52)	.042
Education	-						
Peers	-		1.24	.012			
Drugs	-						
Leisure	-						
Personality (modified)[b]	-		1.48	.004			
Attitudes	-				1.24	(1.06, 1.44)	.006
AUC (95% CI)		.629 (.576, .682)		.614 (.560, .667)			.656 (.602, .710)
AIC		615.3		611.6			605.6
BIC		640.7		624.3			635.2
pseudo r^2		.037		.034			.056
10-fold cross-validated AUC (95% CI; average training sample n=452)							.645 (.582, .708)

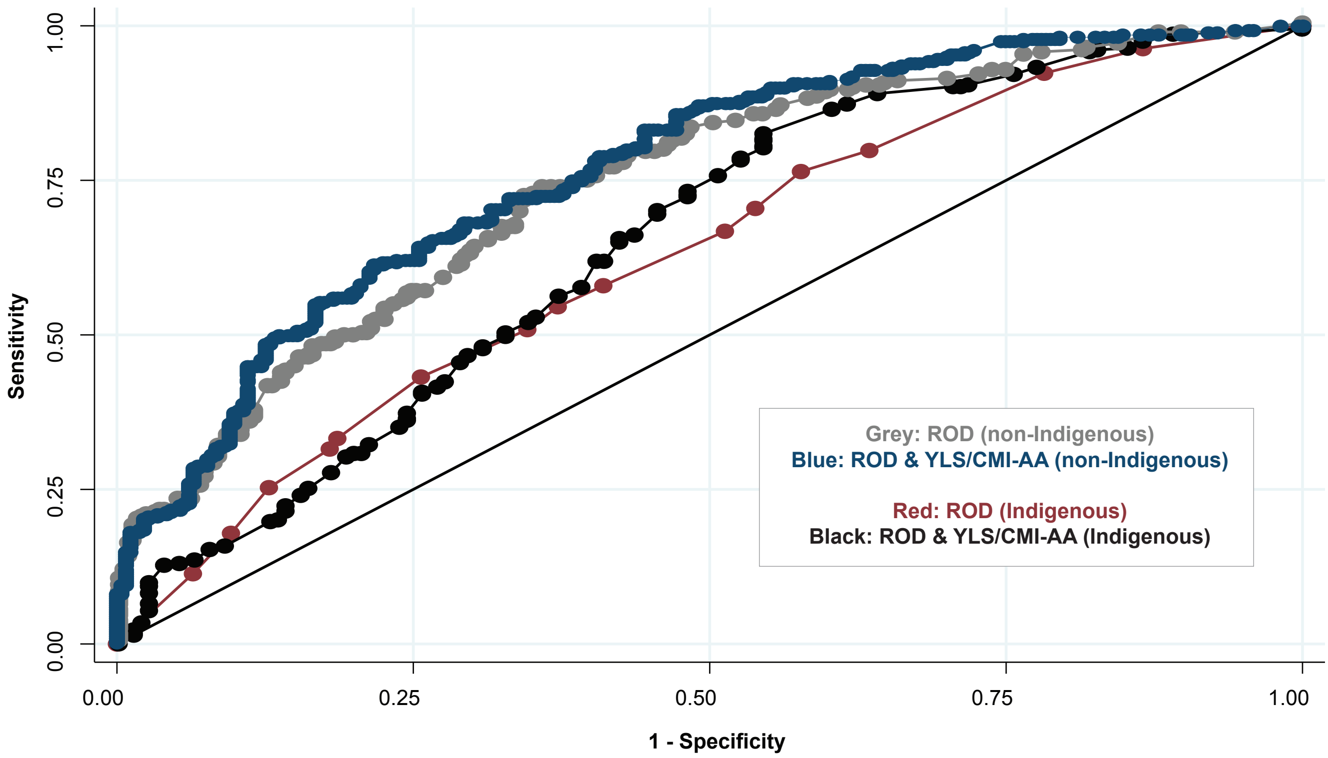
Note. - = Term was not input to the model. Overall likelihood ratio chi-square test *p<.05, **p<.01, ***p<.001
a. Dichotomous: Medium/High (2-7) vs. Low (0-1).
b. Ordinal: High (3-7) vs. Medium (1-2) vs. Low (0).

Model validation

Figure 1 presents the Receiver Operating Characteristic (ROC) curves for the ROD and combined recidivism models (see Tables 3 and 4). ROC plots the proportion of true positives (offenders who were predicted to reoffend and did; sensitivity) against the proportion of false positives (offenders who were predicted to reoffend and did not; 1-specificity; Ringland, 2011). The combined models offer marginal, limited, and non-significant improvements in predictive performance over the respective ROD models, and poorer performance at low sensitivity levels. The non-Indigenous models performed better than the Indigenous models at all except the highest sensitivity levels.

Cross-validated AUCs were slightly lower than the native AUCs for both combined models but remained within the acceptable level for non-Indigenous offenders and below the acceptable level for Indigenous offenders. Variation in CV-AUCs using different fold counts and different seeds randomising the folding process was examined and was not substantive. AUCs for the combined models for the 2013 community-supervised offender cohort were found to be substantially lower for non-Indigenous offenders (.665, 95% CI (.621, .709), n=584) and higher for Indigenous offenders (.678, 95% CI (.633, .723), n=565). In summary, the combined model had limited discriminative power for Indigenous youths and may not perform well in an external sample.

Figure 1. Area Under the ROC Curve for ROD-only and combined models



DISCUSSION

The first aim of the study was to build a model of recidivism based on static predictors from the Bureau's Re-offending Database (ROD, e.g. Smith, 2010). Familiar predictors of recidivism were identified, including early onset of offending and multiple concurrent offences. However, significant interactions between Indigenous status and criminal history necessitated separate models for Indigenous and non-Indigenous offenders. Number of prior finalisations, for example, predicted recidivism only for non-Indigenous offenders. The AUC for the non-Indigenous ROD-only model (.740, 95% CI (.698, .781)) was within the band which Hosmer and Lemeshow (2000) classify as acceptable (0.7-0.8). The AUC for the non-Indigenous ROD-only model (.629, 95% CI (.576, .682)) fell below the acceptable range. Prior criminal justice contacts may do less to differentiate recidivists from non-recidivists in a more entrenched sample of Indigenous offenders.

The second aim of the study was to examine the relationship of YLS/CMI-AA scores to recidivism. With one exception (the *Drugs* subscale, for Indigenous offenders) the YLS/CMI-AA total risk/needs score and its eight subscales were significantly associated with recidivism at the bivariate level for both Indigenous and non-Indigenous offenders. The YLS/CMI-AA risk/needs level also showed strong, positive relationships with recidivism for both groups. When the joint effects of the YLS/CMI-AA subscales were included in a regression model, only two of the seven dynamic subscales – *Family (modified score)* and *Attitudes* – predicted recidivism for Indigenous offenders; these two subscales as well as the *Offences* subscale predicted recidivism for non-Indigenous offenders. In each case, the independent association of these subscales with recidivism was comparatively small. As with the ROD-only models, predictive performance of the YLS/CMI-AA models was acceptable for non-Indigenous offenders and not for Indigenous offenders.

The third and primary aim of the study was to test whether YLS/CMI-AA data predicts recidivism over and above static predictors. The results provide no reason to believe that including subscale scores or the total risk/needs score in the combined model materially improve its ability to discriminate recidivists from non-recidivists for either Indigenous or non-Indigenous offenders. The AUCs for the combined models exceeded those of the respective ROD-only models, however the confidence intervals and point estimates of these models overlapped, indicating that the differences in discriminative power were non-significant.

The dynamic risk subscales that were found to predict recidivism could potentially be used to enhance quasi-experimental studies by suggesting additional controls that might reduce the unobserved differences between treated and untreated offenders (Ringland, 2011). The fact that the same two dynamic subscales were retained in both the Indigenous and non-Indigenous models also suggests that these measures have some cross-cultural predictive validity. It would be prudent to examine the relevance of these and the other subscales with other samples, given that all YLS/CMI-AA subscales have strong theoretical links to recidivism. Furthermore, while excluding subscales that do not predict recidivism improves parsimony and accuracy, these subscales are naturally weighted by the instrument to generate the total risk/needs score and were not designed to be separated in recidivism models.

In this study, YLS/CMI-AA data did little if anything to improve the ability of static-risk based models to discriminate recidivists from non-recidivists; however, validation analyses of the combined model raise doubts about its broader validity. The CV-AUCs were acceptable for the non-Indigenous model but below the acceptable range for the Indigenous model. The poorer predictive performance of the YLS/CMI-AA for Indigenous offenders (compared with non-Indigenous offenders) echoes the earlier validity analyses by Thompson and McGrath (2012).

One limitation of the current study is that the sample was restricted to cases with a valid YLS/CMI-AA to ensure that its dynamic factors would relate reasonably well in time to the individual's offending. One downside to this approach is that the results cannot be generalised to the 235 offenders who did not have a valid YLS/CMI-AA. Offenders with only a prospective YLS/CMI-AA were also included (mean time lag from index appearance to date of YLS/CMI-AA: 15 days). Excluding those offenders would have reduced the sample size beyond that required for the modelling undertaken in this study. Furthermore, most items in the YLS/CMI-AA risk/needs assessment are also intended to cover the 12 months prior to the assessment (Department of Justice, 2014). Finally, sample size was insufficient to explore whether the YLS/CMI-AA could improve the prediction of recidivism by male or female offenders, and this remains an open question. Prior studies offer conflicting findings as to whether the predictive validity of the YLS/CMI-AA varies significantly by gender (Schwalbe, 2008) or does not (Thompson & McGrath, 2012).

The current findings suggest that YLS/CMI-AA data do not significantly improve prediction by static risk-based models of recidivism. That is not to say that dynamic risk factors have no further value. Dynamic risk factors provide information which is crucial in analysing the causes of offending behaviour and selecting an appropriate form of intervention. As Taxman and Caudy (2015) note, dynamic risk factors can enable case management to mitigate static risks. We concur with Caudy et al.'s (2013) suggestion that justice agencies should distinguish risk prediction from risk/needs assessment, and specifically, that dynamic risk factors should only be included in risk prediction models if they increase the predictive validity of those models.

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NOTES

1. This Bulletin uses terminology common to the recidivism risk assessment literature. There is a push to align this terminology with epidemiological research by defining 'predictors' as measures that are correlated with and precede the outcome (recidivism), 'risk factors' as modifiable predictors, and 'risk markers' as predictors that cannot be changed through intervention (Monahan & Skeem, 2016).
2. The term 'dynamic risk' can also be used to refer to *change* in risk, rather than to distinguish static from dynamic risk factors. Changes in risk scores may have unique predictive validity. This could not be explored in the current sample as too few cases had multiple valid YLS/CMI-AA entries.
3. Within RNR, the responsivity principle requires that treatment give consideration to offenders' abilities and learning styles, and their specific individual psychosocial characteristics (Andrews & Bonta, 2007).
4. Widening the selection window to allow up to one month's difference between order start dates in the Juvenile Justice data and ROD increased the sample size of offenders with a valid YLS/CMI-AA by approximately one per cent.
5. This categorisation was used to most evenly group the offences whilst capturing their non-linear relationship with recidivism.
6. The use of override was infrequent (<2% offenders) and did not affect the YLS/CMI-AA scores included in the models in this study. Significant negative associations were observed with recidivism for the strength subtotal and family item but these did not improve the multivariate models.
7. Indigenous offenders comprised significantly ($p<.05$) higher proportions (vs. non-Indigenous offenders) of offenders who: were aged under 15; were aged under 13 at first finalisation;

had any concurrent offences; had more than five prior finalisations; and, had a history of custody.

8. This paper reports the results of 10-fold cross-validation with a pre-set seed to enable replication. Analyses were repeated using 2, 5, and 20 folds and different seeds randomising the folding process to confirm that substantive results were not fold- or seed-dependent.

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