



The prediction of criminal recidivism using routinely available file information

La predicción de la reincidencia delictiva
usando información de archivos
rutinariamente disponibles



Research

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ABSTRACT

Objective. The aim of the present study was to cross-validate the investigation of Buchanan and Leese (2006) into the prediction of criminal recidivism. **Method.** The sample comprised offenders in the criminal justice system of the Canton of Zürich – Switzerland, who were discharged to the community. Participants were followed, and evidence of subsequent charges and convictions for both general and serious recidivism was investigated at fixed periods of 2.5, 6.5, and 10.5 years. The predictive validity of socio-demographic, criminal history, and legal class information was assessed using logistic regression as well as log-likelihood, receiver operating characteristic curve, and contingency analyses. **Results.** A multivariable model including age and criminal history information was found to produce the highest rates of predictive validity for general and serious recidivism. **Conclusion.** Information regularly accessible in forensic practice may be able to guide clinicians as to the recidivism risk level of their patients.

Key Words:

Risk Assessment,
Violence, Forensic,
Recidivism

RESUMEN

Objetivo: El objetivo del presente estudio fue el de cross-VALIDAR la investigación de Buchanan y Leese (2006) en la predicción de la reincidencia criminal. **Método.** La muestra constó de delincuentes en el sistema de justicia penal del Cantón de Zürich – Suiza, quienes fueron dados de alta a la comunidad. Los participantes fueron seguidos, y la evidencia de los cargos posteriores y condenas por reincidencia general y grave se investigó en períodos fijos de 2.5, 6.5 y 10.5 años. Se evaluó la validez predictiva de la historia criminal socio- demográfica e información de clase legal mediante regresión logística, así como el logaritmo de verosimilitud, la curva ROC, y análisis de contingencia. **Resultados.** Se encontró un modelo multivariable que incluye la edad y la información de antecedentes penales para producir los más altos índices de validez predictiva de reincidencia. **Conclusión.** Información habitualmente accesible en prácticas forenses puede ser capaz de guiar a los médicos respecto al nivel de riesgo de reincidencia de sus pacientes.

Palabras Clave:

Evaluación de
riesgos, Violencia,
Forense,
Reincidencia

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1. INTRODUCTION

Since the number of forensic hospital beds has increased for the last two decades in many Western countries (Priebe et al., 2008), it could be argued that identifying accurate and reliable methods of violence risk assessment in psychiatric populations is more important now than ever. Although the use of complex violence risk assessment instruments is recommended by current clinical guidelines, the practical usefulness of such schemes is limited by costliness, training requirements, time consumption, and, above all, a lack of access to the necessary information to administer the schemes (Hawley, Gale, Sivakumaran, & Littlechild, 2010; Khirya, Weaver, & Maden, 2009; Viljoen, McLachlan, & Vincent, 2010). Thus, some researchers have investigated the utility of routinely accessible file information as a proxy in the risk assessment process (Singh, Grann, Lichtenstein, Långström, & Fazel, 2012; Wootton et al., 2008). Recently, Buchanan and Leese (2006) tested “the applicability of a statistical approach used elsewhere in medicine to the quantification of the contributions made by different kinds of information in the prediction of criminal conviction” (p. 476) among psychiatric patients discharged from high secure hospitals in the United Kingdom. The researchers found evidence supporting the predictive validity of select socio-demographic and criminal history information in this task, and recommended further investigation in similar samples. Due to the differences in culture as well as criminal justice systems based on common law versus civil law, it is uncertain whether these findings generalize to central European nations such as Switzerland.

The aim of the present study was to attempt to cross-validate Buchanan and Leese’s findings concerning the robust prediction of general and serious recidivism using routinely available file information in a total forensic cohort from the Canton of Zürich, Switzerland.

2. METHOD

2.1. Participants

Participants in the present investigation included offenders from the Zürich Forensic Study, which examined all violent (including sexual) offenders enrolled in probation and/or correction services of the criminal justice system in the Swiss Canton of Zürich in August 2000 ($N = 465$). The sample was modified to match that investigated by Buchanan and Leese such that only offenders who were diagnosed with a DSM-

IV or ICD-10 diagnosis of a mental disorder¹ and were followed in the community for at least 2.5 years were included ($N = 204$). This sample excluded a small group of women offenders ($n = 5$) as well as men who died or were deported prior to the 2.5-year minimal follow-up ($n = 6$). Thus, the present sample was comprised of 193 men diagnosed with a mental disorder discharged to the community.

2.2. Procedure

Five Master’s-level psychologists collected socio-demographic, criminal history and mental health information for participants via clinical and correctional file reviews. The files contained comprehensive personal details, including information on both previous and index offenses as well as psychiatric diagnoses. In a pilot study on a subsample of participants from the Zürich Forensic Study ($n = 30$, 6.5%), the interrater agreement for the collected information was found to be high ($\kappa = 0.70$; Landis, & Koch, 1977), this represents a “substantial” (p. 165) level of reliability. Recidivism was assessed based on criminal records, which included information on charges and convictions.²

Criminal records were evaluated for evidence of recidivism every two to three years, the final evaluation taking place in May 2011. Similar to Buchanan and Leese, two forms of recidivism were used as outcomes: general (any charge or conviction after the index offense) and serious offending (a charge or conviction for a violent [including sexual] offense after the index offense).

2.3. Materials

The multivariable model under investigation was designed by Buchanan and Leese to use routinely available file information to predict recidivism. The model was composed of the following three independent variables:

- a) Gender
- b) Age at discharge
- c) Number of prior convictions at the time of discharge

In its development study, the model was found to be a valid predictor of both general and serious recidivism within 2.5, 6.5, and 10.5 years after discharge. Adding information on the legal class of participants’ psychiatric diagnosis (mental illness, personality disorder or mental impairment) was not found to significantly increase the predictive validity of the model when general recidivism was the outcome; however, information on legal class did result in

¹ In Switzerland, those legally classified as having a mental illness were diagnosed via expert opinion.

² In Switzerland, charges are displayed in criminal records only while individuals are under investigation.

Table 1. Logistic regression analyses exploring the ability of routinely available file information to predict recidivism risk

Follow-up	Model	Outcome					
		General Recidivism			Serious Recidivism		
		OR	95% CI	p	OR	95% CI	p
2.5 years (N = 193)	Age alone	0.96	0.93-0.99	0.01*	1.02	0.97-1.08	0.45
	Age and prior conviction						
	Age	0.95	0.92-0.99	0.01**	1.02	0.97-1.08	0.46
	Prior convictions	1.20	1.09-1.33	0.001***	2.25	0.58-8.71	0.24
	Age, prior conviction, and legal class						
	Age	0.95	0.92-0.99	0.01**	1.02	0.96-1.08	0.50
6.5 years (N = 180)	Age alone	0.96	0.93-0.99	0.01**	0.99	0.95-1.03	0.65
	Age and prior conviction						
	Age	0.95	0.92-0.98	0.01**	0.99	0.95-1.03	0.54
	Prior convictions	1.22	1.09-1.36	0.001***	3.70	1.45-9.42	0.01**
	Age, prior conviction, and legal class						
	Age	0.95	0.92-0.98	0.01**	0.99	0.95-1.03	0.54
10.5 years (N = 135)	Age alone	0.96	0.93-0.99	0.02*	0.98	0.95-1.02	0.34
	Age and prior conviction						
	Age	0.95	0.92-0.99	0.01**	0.98	0.94-1.01	0.21
	Prior convictions	1.27	1.09-1.48	0.01**	3.66	1.61-8.33	0.01**
	Age, prior conviction, and legal class						
	Age	0.96	0.92-0.99	0.02*	0.97	0.94-1.01	0.18

Note. OR = odds ratio, CI = confidence interval, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Serious recidivism was operationally defined as a charge or conviction for a violent (including sexual) offense. Legal class = mental illness and/or personality disorder. Fractional polynomials were used to confirm the linearity in the logic for all continuous variables.

incremental validity for the prediction of serious recidivism.

For the purposes of the present study, whether or not participants had been convicted of any crime (for the prediction of general recidivism) or any violent (including sexual) crime (for the prediction of serious recidivism) prior to their index offense was used in place of the “number of prior convictions at the time of discharge” item. The use of such dichotomous proxies was judged to be appropriate, as Buchanan and Leese found their sample to have a median of two offences at the time of their discharge. Albeit Buchanan and Leese investigated the association between the legal class of mental impairment and recidivism, the contribution of this variable was not assessed, as only two participants in the present sample met this criterion and neither was discharged during the study inclusion period. Thus, legal class was being classified as having a diagnosable mental illness (substance abuse

or dependence, schizophrenia spectrum disorders, mood disorders, anxiety disorders, and adjustment disorder) and/or personality disorder.

2.4. Statistical Analyses

Data analysis for the present study was modeled after that of Buchanan and Leese, and took place in three stages. In the first stage, the predictive validity of combinations of the collected age, prior conviction, and legal class information was assessed using odds ratios produced by multivariable logistic regression analyses. The base model for the calculations included only offender age, and evidence for incremental validity was investigated using log likelihood analyses when prior conviction and legal class information were added. Linearity in the log of continuous variables was confirmed *a priori*. In the second stage, receiver operating characteristic (ROC) curve analyses were used to calculate areas under the

curve (AUC) produced by the same multivariable models from the first stage. In the third stage, both the median score on each model as well as the inflection point of the ROC curve (i.e., the cut-off score that balanced the cost-ratio between true and false positive rates) for each model were used to calculate sensitivity (the percentage of recidivists judged to be at high risk), specificity (the percentage of non-recidivists judged to be at low risk), the number needed to detain (NND; the number of participants judged to be at high risk who would need to be detained to prevent a single incident of community recidivism from occurring), and the number safely discharged (NSD; the number of

participants judged to be at low risk who could be discharged to the community prior to a single incident of recidivism). For a detailed discussion of these discrimination (AUC, sensitivity, specificity) and calibration (NND and NSD) statistics, see Singh (2013). Effect estimates were calculated using general or serious recidivism as outcomes, and fixed lengths of follow-up of 2.5, 6.5, and 10.5 years. All analyses were conducted using STATA/IC 12.1 for Windows (StataCorp, 2012) using two-tailed statistical tests and a standard statistical significance threshold of $\alpha=0.05$.

Table 2. Likelihood, ROC, and contingency analyses exploring the discrimination and calibration validity of routinely available file information in the prediction of recidivism

Follow-up	Recidivism	Model	Likelihood		ROC	Contingency (Median score)		Contingency (Cost-ratio)		NND	NSD		
			-2LL	p (increase)	AUC	Sens	Spec	Sens	Spec				
2.5 years (N = 193)	General	Constant	224		0.50								
		A	216	0.01	0.62	0	100	63	59	2.8	5.3		
		A+C	200	<0.001	0.74	20	97	67	66	2.4	6.7		
		A+C+D	200	NS	0.74	22	97	65	65	2.5	6.3		
	Serious	Constant	78		0.50								
		A	72	NS	0.61	0	100	56	69	12.5	33.3		
		A+C	70	NS	0.63	0	100	56	63	14.3	33.3		
		A+C+D	70	NS	0.64	0	100	56	64	14.3	33.3		
	6.5 years (N = 180)	General	Constant	246		0.50							
			A	234	<0.01	0.64	43	78	60	60	1.9	2.9	
			A+C	220	<0.001	0.75	55	82	68	72	1.6	4.0	
			A+C+D	218	NS	0.76	56	79	68	70	1.6	3.8	
Serious		Constant	139		0.50								
		A	134	NS	0.54	0	100	68	37	7.7	9.1		
		A+C	126	<0.01	0.68	0	100	68	60	5.3	14.3		
		A+C+D	126	NS	0.68	0	100	73	57	5.3	16.7		
10.5 years (N = 135)		General	Constant	176		0.50							
			A	170	<0.02	0.62	94	14	56	65	1.4	1.9	
			A+C	156	<0.001	0.76	89	45	67	67	1.3	2.2	
			A+C+D	156	NS	0.77	89	47	68	73	1.2	2.3	
	Serious	Constant	154		0.50								
		A	150	NS	0.55	0	100	62	49	3.4	4.8		
		A+C	140	<0.01	0.68	6	99	65	65	2.6	6.3		
		A+C+D	140	NS	0.68	3	98	65	65	2.6	6.3		

Note. -2LL = -2Log-likelihood ratio, ROC = receiver operating characteristic, AUC = area under the curve, Median score = median score used as cut-off threshold, Cost-ratio = score that optimized the balance between sensitivity and specificity used as cut-off threshold, Sens = sensitivity, Spec = specificity, NND = number needed to detain, NSD = number safely discharged, A = age, C = criminal conviction prior to index offense, D = legal class (mental illness and/or personality disorder), - = not applicable, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Serious recidivism was operationally defined as a charge or conviction for a violent (including sexual) offense.

3. RESULTS

3.1. Sample Characteristics

The present sample was composed of 193

male violent (including sexual) offenders with DSM-IV or ICD-10 diagnoses of mental disorders who were discharged into the community for at least 2.5 years. Of the total sample, 180 participants had a follow-up length of at least 6.5 years and 135 had a follow-up



period of at least 10.5 years. Criminal registers were used to evaluate evidence of recidivism at 2.5 ($N_{\text{Total}} = 193$, $n_{\text{General Recidivism}} = 52$ [26.9%], $n_{\text{Serious Recidivism}} = 10$ [5.2%]), 6.5 ($N_{\text{Total}} = 180$, $n_{\text{General Recidivism}} = 78$ [43.3%], $n_{\text{Serious Recidivism}} = 23$ [12.8%]), and 10.5 years ($N_{\text{Total}} = 135$, $n_{\text{General Recidivism}} = 86$ [63.7%], $n_{\text{Serious Recidivism}} = 35$ [25.9%]). As the demographic, psychiatric, and criminal history composition of the three nested samples were not significantly different according to paired-samples t -tests and χ^2 tests, descriptive characteristics for the largest sample ($N = 193$) are reported below.

The mean age of participants upon discharge was 39.2 years ($SD = 11.6$), and almost 2/3 of the sample ($n = 126$, 65.6%) had been convicted prior to the index offense. Regarding the psychiatric composition of the sample, diagnoses included personality disorder ($n = 85$, 44.0%), substance abuse or dependency ($n = 68$, 35.2%), and schizophrenia-spectrum disorder ($n = 33$, 17.1%). In Switzerland, expert opinion is used to determine which number of services (e.g., inpatient hospitalization, outpatient treatment, counseling, medication) is allocated to offenders whose mental illness (es) is deemed treatable and related to increased recidivism risk. As part of their sentence, the majority of participants ($n = 141$, 73.1%) in the present study were mandated some form of court-ordered therapy.

3.2. Prediction of General Recidivism

When general recidivism was the outcome of interest, younger age and having a conviction prior to the index offense were significant predictors (Table 1). Legal class did not add significantly to the predictive ability of age and prior conviction for general recidivism. Across 2.5, 6.5, and 10.5 years of follow-up, there was a 5% decrease in general recidivism likelihood for every year increase in age and between a 20% and 27% increase in general recidivism likelihood if an offender had a prior general conviction. Log-likelihood analyses confirmed that prior conviction added significant incremental validity to a model composed only of age at discharge (Table 2), and ROC curve analyses found that a model of prior conviction and age had acceptable discrimination validity (AUCs between 0.74 and 0.76) according to criteria established by Hosmer & Lemeshow (2000). Using a cut-off threshold of $P=0.5$, lower rates of specificity (0.03 to 0.55) were found across follow-up periods compared to rates of sensitivity (0.11 to 0.80). When the inflexion point of the ROC curve for this model was used as the threshold, the resulting tool balanced sensitivity and specificity: Between 67% and 68% of recidivists and between 66% and 72% of non-recidivists were correctly classified by the

scheme, depending on the length of follow-up. Between 1.3 and 2.4 individuals who were judged to be at high risk by the model would need to be detained to prevent a single incident of general recidivism (NND) and between 2.2 and 6.7 individuals who were judged to be at low risk could be safely discharged prior to a single incident of general recidivism (NSD).

3.3. Prediction of Serious Recidivism

When serious recidivism was used as an outcome in logistic regression analyses, only prior conviction was significantly predictive at 6.5 and 10.5 years after discharge (Table 1); for 2.5 years, no model significantly predicted likelihood of serious recidivism. Up to a 2% decrease in serious recidivism likelihood for every one year increase in age was found for 6.5 and 10.5 years after discharge. A 266-270% increase in serious recidivism likelihood was found if an offender had a prior serious conviction at 6.5 and 10.5 years post discharge.

Log-likelihood analyses verified that prior conviction added significant incremental validity to age alone for 6.5 and 10.5 years follow-up (Table 2). For 2.5 years follow-up, prior convictions (and legal class) did not add significantly to age alone. ROC curve analyses determined that a model composed of prior conviction and age for 6.5 and 10.5 years had moderate discrimination validity (AUCs of 0.68). Adopting a cut-off of $P=0.5$ for the bivariate model resulted in maximal rates of specificity (0.99 to 1.00) and minimal rates of sensitivity (0.00 to 0.06) across all lengths of follow-up. Using the inflexion point of the ROC curve for this model as the cut-off threshold resulted in a tool that correctly classified between 65% and 68% of serious recidivists and between 60% and 65% of non-recidivists. Between 2.6 and 5.3 individuals who were judged to be at high risk by the model would need to be detained to prevent a single incident of serious recidivism (NND) for 6.5 and 10.5 years after discharge. The number of people judged to be at low risk who could be safely discharged prior to a single incident of serious recidivism was found to be between 6.3 and 14.3 (NSD) at 6.5 and 10.5 years.

3.4. Comparison with Original Study Findings

Findings were consistent with those of Buchanan and Leese: The AUCs and NNDs found for 2.5 (AUC = 0.68, NND = 2.2), 6.5 (AUC = 0.73, NND = 2.2), and 10.5 years (AUC = 0.72, NND = 2.1) using age, gender and prior convictions for general recidivism as the outcome. Legal class did not add significantly to the predictive accuracy of age, gender and prior convictions. The present study found AUCs and NNDs of 0.74 and 2.4 for 2.5 years, 0.75 and 1.6 for 6.5 years, and 0.76 and 1.3 for 10.5 years using age and prior convictions for general recidivism as the outcome. Adding information on legal class also did

not add significantly to age and prior convictions. The findings for serious recidivism within 10.5 years after discharge (AUC = 0.69, NND = 4.9)³ were similar to those found by the present study authors for 10.5 years (AUC = 0.68, NND = 2.6). However, Buchanan and Leese found legal class to significantly add to the incremental validity of age, gender and prior convictions at 10.5 years, which the present study did not.

4. DISCUSSION

The present study further investigated the findings of Buchanan and Leese into the prediction of criminal recidivism using routinely available file information. In their original report, the researchers demonstrated the usefulness of four readily available types of information (gender⁴, age, criminal history, and legal class) in assessing recidivism risk amongst forensic psychiatric patients, and suggested replication in additional samples. Thus, the aim of the present study was to attempt to cross-validate the association between predictors for criminal recidivism reported by Buchanan and Leese as well as serious recidivism in a total forensic cohort from the Canton of Zürich, Switzerland. Our findings confirm that a combination of two of the "Big Four" (Andrews, & Bonta, 2010) risk factors for recidivism, young age and criminal history, may be the most useful pieces of accessible clinical information in assessing risk.

4.1. Implications and Future Directions

The findings of the present investigation hold potentially important implications for both clinicians and researchers. First, given how costly and time-consuming structured risk assessments can be (Viljoen et al., 2010), using routinely available information on age and criminal history to preliminarily assess the risk of recidivism in offender populations might be useful in initially screening as to whether a more formal risk assessment is necessary (Singh et al., 2012). Second, that legal class was not found to add incrementally to the predictive ability of age and prior convictions is consistent with meta-analytic findings, which suggests that predictors of recidivism are the same for offenders with and without mental illness (Bonta, Law, & Hanson, 1998). In contrast to Buchanan and Leese, who found legal class to add

significantly to the predictive ability for serious recidivism at 10.5 years, the present study did not find legal class to add significantly to age and prior convictions, which might be due to the difference in participants. Future research might investigate whether the inclusion of specific disorders (e.g., antisocial personality disorder) contribute incrementally to the prediction of recidivism. Third, as predictive validity effect estimates for discrimination (e.g., AUC) and calibration validity (e.g., NND and NSD) were similar to those for formal risk assessment instruments (Fazel, Singh, Doll, & Grann, 2012), this suggests that if the sole aim of risk assessment is to produce high psychometric properties, then complex schemes are not necessary. Hence, perhaps the time has come to shift focus from attempting to maximize prediction accuracy to formulation and management, identifying treatment targets and markers of offender responsibility to tailor interventions (Hart, & Logan, 2011).

4.2. Limitations

There are several potential limitations to the present investigation. First, necessary adaptations were made to the models examined by Buchanan and Leese. Specifically, whether or not participants had been convicted of a crime prior to their index offense was used rather than the number of prior convictions at the time of discharge. The fact that we still found similar results to those of Buchanan and Leese suggests the robustness of criminal history information in the prediction of recidivism risk. Second, a related limitation was that the association between the legal class of mental impairment and recidivism could not be assessed because only two participants met this criterion. Third, we included both charges as well as convictions as our outcome criteria, whereas Buchanan and Leese included only convictions. This increased the sensitivity of our model, hence the higher base rates of both general (63.7%) and serious recidivism (25.9%) at 10.5 years than those obtained by the original authors (32% general and 14% serious recidivism). Also, the participants of our study were all released to the community, while 66% of patients in the Buchanan and Leese sample were released to other hospitals. Fourth, only criminal records were used to identify cases of recidivism, which may have potentially underestimated the prevalence of violent incidents in the sample. Using a combination of criminal records, self-report, and collateral information (e.g., friends and family members) is recommended (Monahan et al., 2001). Finally, no model was significant to predict the likelihood of serious recidivism within 2.5 years, which might be because serious offences can take up to a year to enter the system, reducing sensitivity for this length of follow-up.

³ Buchanan and Leese (2006) did not report serious recidivism findings for 2.5 or 6.5 year follow-up periods, and also did not calculate the NSD, as it was before the development of the performance indicator by Fazel and colleagues (2012).

⁴As we only included male offenders, there was no need to statistically adjust for the effects of gender.



5. CONCLUSION

The present study found that the use of routinely available file information on offenders' age and criminal history may be able to discriminate between recidivists and non-recidivists just as well as more complex schemes. Such information is routinely incorporated into commonly used risk assessment instruments (Singh, Serper, Reinharth, & Fazel, 2011), this suggests that the use of complex assessment schemes is perhaps best justified by the need to develop and monitor risk management plans. Accordingly, such a shift may result in renewed interest in both the mechanisms behind interactions in dynamic risk and protective factors as well as in the systematic identification of those individuals who are versus those who are not likely to experience changes in dynamic risk. By relying on a few pieces of clinically accessible information to establish an *absolute* level of risk and then structured instruments to evaluate changes in offenders' *relative* threshold of risk, clinicians may be better able to inform their immediate and short-term risk assessment decision.

6. REFERENCES

- Andrews, D. A., & Bonta, J. (2010). Rehabilitating criminal justice policy and practice. *Psychology, Public Policy and Law*, 16, 39-55.
- Bonta, J., Law, M., & Hanson, K. (1998). The prediction of criminal and violent recidivism among mentally disordered offenders: A meta-analysis. *Psychological Bulletin*, 123, 123-142.
- Buchanan, A., & Leese, M. (2006). Quantifying the contributions of three types of information to the prediction of criminal conviction using the receiver operating characteristic. *The British Journal of Psychiatry*, 188(5), 472-478.
- Fazel, S., Singh, J. P., Doll, H., & Grann, M. (2012). The prediction of violence and antisocial behaviour: A systematic review and meta-analysis of the utility of risk assessment instruments in 73 samples involving 24,827 individuals. *British Medical Journal*, 345, e4692.
- Hart, S. D., & Logan, C. (Eds.). (2011). *Formulation of violence risk using evidence-based assessments: The structured professional judgement approach*. Chichester, UK: John Wiley & Sons, Ltd.
- Hawley, C. J., Gale, T. M., Sivakumaran, T., & Littlechild, B. (2010). Risk assessment in mental health: Staff attitudes and an estimate of time cost. *Journal of Mental Health*, 19, 88-98.
- Hosmer, D. W., & Lemeshow, S. (2000). *Applied logistic regression*. New York: Wiley.
- Khiroya, R., Weaver, T., & Maden, T. (2009). Use and perceived utility of structured violence risk assessments in English medium secure forensic units. *Psychiatrist*, 33, 129-132.
- Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, 33, 159-174.
- Monahan, J., Steadman, H. J., Silver, E., Appelbaum, P. S., Robbins, P. C., Mulvey, E. P., ... Banks, S. (2001). *Rethinking risk assessment: The MacArthur Study of mental disorder and violence*. New York: Oxford University Press.
- Priebe, S., Frottier, P., Gaddini, A., Kilian, R., Lauber, C., Martínez-Leal, R., ... Wright, D. (2008). Mental health care institutions in nine European countries, 2002 to 2006. *Psychiatric Services*, 59(5), 570-573.
- Singh, J. P. (2013). Predictive validity performance indicators in violence risk assessment: A methodological primer. *Behavioral Sciences & the Law*, 31, 8-22.
- Singh, J. P., Serper, M., Reinharth, J., & Fazel, S. (2011). Structured assessment of violence risk in schizophrenia and other disorders: A systematic review of the validity, reliability, and item content of 10 available instruments. *Schizophrenia Bulletin*, 37, 899-912.
- Singh, J. P., Grann, M., Lichtenstein, P., Långström, N., & Fazel, S. (2012). A novel approach to determining violence risk in schizophrenia: Developing a stepped strategy in 13,806 discharged patients. *PloS one*, 7, e31727.
- StataCorp. (2012). *Stata 12.1 statistical software*. College Station, TX: StataCorp LP.
- Viljoen, J. L., McLachlan, K., & Vincent, G. M. (2010). Assessing violence risk and psychopathy in juvenile and adult offenders: A survey of clinical practices. *Assessment*, 17, 377-395.
- Wootton, L., Buchanan, A., Leese, M., Tyrer, P., Burns, T., Creed, F., ... Walsh, E. (2008). Violence in psychosis: Estimating the predictive validity of readily accessible clinical information in a community sample. *Schizophrenia Research*, 101, 176-184.