Predictors of Recidivism Following Release from Custody: A Meta-Analysis

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Abstract

The reliable identification of those offenders at greatest risk of post-release recidivism is critically important given the emotional and financial costs associated with offending behaviour. The aim of the current study was to synthesise the available literature on risk predictors to identify which factors are predictive of recidivism in adult offenders, in the four years following release from custody. After systematically reviewing the literature and selecting those at least risk of bias, 43 high quality studies were subjected to meta-analysis. Sufficient data pertaining to 21 factors were available. Consistent with Bonta and Andrews (2017), prominent factors associated with the 'central eight' risk domains for general recidivism, particularly those indicative of antisocial potential, produced the largest effect sizes. These included factors such as an extensive criminal history (e.g., number of previous incarcerations), rule violations whilst under supervision, and holding procriminal attitudes. Overall, static risk factors were superior to dynamic in predicting recidivism. We explore these findings in the context of the limitations of the risk predictor literature and argue that ongoing behavioural monitoring is a promising means of identifying real-time changes in the antisocial potential of prisoners released to the community.

Keywords: recidivism; release; custody; meta-analysis; risk factors.

Introduction

A substantial body of literature supports the notion that antisocial behaviour broadly follows one of two developmental courses from adolescence into adulthood (Caspi & Moffitt, 1995; Moffitt, 1990, 1993, 1994, 1997, 2006). Moffitt (1993) suggests that many people behave antisocially in adolescence, but in only a subset - known as life-course persistent offenders - does this behaviour become stable and persistent. Moffitt (2005) attributes 50% of crimes in the United States to 10% of families, whilst in a Swedish study, Falk et al. (2014) found that 1% of the population accounted for 63% of the violent crimes committed over the 37-year study period. It is also claimed that there is a sub-group comprising offenders undeterred by the consequences of their crimes (Crank & Brezina, 2013; Sampson & Laub, 2003). It is therefore urgent and necessary to develop the means of distinguishing single episode offenders from those likely to persist in their criminal behaviour, so that correctional professionals can intervene and reduce the risk of harm to the public (cf. Janus & Prentky, 2003). Moreover, on release to the community, criminal justice professionals often have to distinguish these individuals quickly - to direct finite resources to the management of those at highest risk of causing harm. These decisions are made in the context of increasing workload demands (DeMichelle & Payne, 2018; Martin & Zettler, 2020); for example over the past 30 years the number of people sentenced to indeterminate sentences has increased three-fold both in the US (The Sentencing Project, 2020) and in the UK (MoJ, 2016).

Predictors of recidivism literature: The current picture

In predicting criminal recidivism, criminal justice professionals now have access to a well-established field of research, integrated via meta-analyses (Bonta et al., 2014; Gendreau et al. 1996; Lipsey & Derzon, 1998). Synthesising this research into a General Personality and Cognitive Social Learning (GPCSL) perspective of criminal behaviour, Bonta and Andrews (2017) conclude that there are essentially a 'central eight' risk factors which distinguish repeat offenders from single episode offenders. These so-called 'criminogenic' factors are as follows: a history of criminal behaviour (early, persistent and varied criminal activity), antisocial personality pattern (impulsive, callous and aggressive disposition), procriminal attitudes (rationalisations for antisocial behaviour), antisocial companions (immediate social support for crime), family/marital (lack of prosocial support and conflictual intimate relationships), school/work (poor engagement, performance and work/study relationships), leisure/recreation (low engagement and satisfaction in prosocial leisure pursuits) and substance abuse. These factors emerge from the offender's proximal social context and indeed, Bonta and Andrews (2017) propose that the density of risk factors positively associates with criminal behaviour. Indeed, combining risk factors shows superior risk prediction (cf. Andrews, 1989), with many contemporaneous risk tools typically yielding moderate-to-large effect sizes (Singh et al., 2011; Tully et al., 2013; Yang et al., 2010). Recent meta-analyses further support that the factors outlined in the GPCSL show the strongest correlations with recidivism across jurisdictions (cf. Eisenberg et al., 2019; Katsiyannis et al., 2018), particularly the four indicators of antisocial potential ('big four': Andrews et al., 2006). For instance, Katsiyannis and colleagues (2018) reviewed predictors of adult recidivism in US adult offender samples between 1994 through 2015 with family criminality, family rearing, antisocial personality, and a history of antisocial behaviour showing the largest effect sizes. Eisenberg and colleagues (2019) drew similar findings from studies of forensic hospital outpatients; their findings supported the notion of a 'central eight' risk factors with criminal history and antisocial pattern showing the greatest relationships with both general and violent recidivism.

Static and dynamic risk factors – conceptual challenges to isolating risk predictors

The 'central eight' risk factors consist of a combination of what Bonta and Andrews (2017) coin *static* and *dynamic* risk factors. These terms distinguish between those factors which simply correlate with recidivism and those which are clinically meaningful. *Static risk factors* are relatively fixed aspects of an offender's history such as age or number of previous convictions. Whilst they are subject to change (e.g., people age, conviction history can worsen), they cannot be changed through behavioural/psychosocial intervention. In contrast, *dynamic risk factors* have the potential for change through correctional programming. That is, there is a theoretical basis to assume that changes or moderations to one's thinking or behaviour might disable routes back into offending (Bonta & Andrews, 2017). Given the blunt and atheoretical nature of static risk factors and potential within the concept of dynamic risk factors to identify and influence the causes of criminal behaviour, there is palpable interest in putting dynamic risk factors at the forefront of risk assessment research.

Indeed, there is some evidence to indicate that dynamic risk factors provide significant incremental predictive value over static risk factors (Allan et al., 2007; Beech et al., 2002; Olver et al., 2007; Thornton, 2002; van den Berg et al., 2018). Yet, this finding is refuted by critics who find that including dynamic risk factors does not improve predictive accuracy once static risk is controlled for: the majority of risk prediction variance is explained by the static/historical factors (Casey, 2016; Caudy et al., 2013; Coid et al., 2009; Morgan et al., 2013).

Problems in the conceptual distinction between static and dynamic risk factors – and how these factors are measured in the field - might explain these findings (Harris & Rice, 2015; Heffernan et al., 2019). Indeed, the conceptual distinction remains hypothesis. Beech and Ward (2004) propose that rather than being distinct entities, static factors act as markers for the past operation of dynamic factors and that both measure correlates of the underlying propensities for offending rather than the causes of offending. Effectively then, they may be measuring the same construct at different temporal points and the superior predictive ability of one over the other is a question of measurement reliability, disadvantaging dynamic risk factors. Heffernan and colleagues (2019) contend that the concept of dynamic risk factors is broad and consists of a variety of contextual (e.g., gang membership), behavioural (e.g., use of weapons) and psychological state aspects (e.g., violent ideation). A single concept (e.g., impulsivity) can be measured in different ways (e.g., go-no go task; observation; self-report) and even where the measurement criterion is prescribed, such as in the case of items on risk assessment tools, subjectivity (cf. Baird, 2009; Beech et al., 2016; Duwe & Rocque, 2016) or reliance on information subject to impression management (cf. Tan & Grace, 2008; Tierney & McCabe, 2001) can affect reliability and validity. Static risk factors, in comparison, are often readily available; and easily and reliably measured (Lehmann et al., 2016).

Where valid and reliable measurement is established, the potential for predictive superiority in dynamic risk factors lies in the 'change' information. If dynamic risk factors change through deliberate intervention and such intervention produces changes in criminal contact (Bonta & Andrews, 2017), then plausibly, post-intervention scores on dynamic risk factors will predict recidivism better than pre-intervention scores (see Harris & Rice, 2015 for a discussion). However, in their meta-analysis of the 'central eight' risk factors, Eisenberg and colleagues (2019) found few studies which measured dynamic risk factors in this way. Dynamic risk factors were frequently measured at a single-time point, effectively operating as static risk factors; a description of the offender's past situation. The dynamic risk information – the very aspect that makes the risk factor changeable – becomes lost (Douglas & Skeem, 2005). Measuring a variable once and calling it dynamic "cannot contribute to progress" (Harris & Rice, 2015, p. 139). Even where dynamic risk factors are measured more than once, Harris and Rice (2015) caution that if the post-intervention score adds to, but does not exceed the predictive ability of the pre-intervention score, the improvement in risk prediction potentially occurs by virtue that measuring twice is more accurate than measuring once. While dynamic factors are more amenable to directing intervention, in the field of risk prediction of violence there is as yet no evidence that they are better risk predictors compared to static factors (Casey, 2016; Harris & Rice, 2015; Heffernan et al., 2019).

Methodological challenges to isolating risk predictors

In addition to the conceptual issues outlined, three other factors affect the identification of the strongest predictors of recidivism; factors which have not been addressed adequately in prior meta-analyses. First, little attention has been paid to the quality of the studies underpinning past meta-analyses. Hayden and colleagues (2013) suggest that prognostic studies are prone to methodological shortcomings. In addition to the aforementioned problems with inconsistent measurement of prognostic factors, it is important to capture a representative sample and to account for confounding measures: issues which might contaminate a meta-analysis with factors that would not, in studies of higher methodological rigour, otherwise predict the outcome of interest. Second, prior meta-analyses tend to present bivariate effects only. Bivariate effect sizes are often artificially inflated and liable to spurious findings when confounding effects have not been accounted for (Ferguson, 2015). Turanovic and Pratt (2020) advocate the presentation of multivariate effect sizes in conjunction with bivariate effects sizes as doing so can 'shed light on issues of spuriousness, appropriate model specification, and help to further understand the conditions under which a statistical relationship is strongest or weakest in the literature' (p.10). Third, whilst it is well-established that variability in the predictive accuracy of violence risk assessment tools is impacted by variability in the samples on which these tools are constructed and validated (cf. O'Shea et al., 2013; Singh et al., 2011; Singh et al., 2014), methodological moderators are largely ignored in meta-analyses focusing on individual risk factors. Singh and colleagues (2014) propose that variances in factors such as the underlying local base-rate for re-offending, the study design (e.g., follow-up time, recidivism measure), and the sentencing and preventative measures employed in different jurisdictions, can all moderate predictive accuracy. Establishing the impact of moderator variables on individual predictors of recidivism is therefore necessary.

The current study

The purpose of the present study was to elucidate from the literature which risk factors are predictive of recidivism during the initial years following release from custody. We purposely targeted samples released from custody as they tend to be more persistent in their criminality, have committed offences of a more serious nature, and have higher rates of recidivism (Ministry of Justice, 2020). Arguably therefore, and in the context of the increased workload demands within Probation Services (DeMichelle & Payne, 2018; Martin & Zettler, 2020), there is urgency in identifying those at higher risk of recidivism among samples pending custodial release. We also focused on a defined follow-up period of six months to four years on the basis that, in those countries that measure recidivism over five years or more, the trajectory of recidivism is steepest up to six months and tails off significantly after three years (Durose et al., 2014; Fazel & Wolf, 2015). By adopting this parameter, the study aimed to identify variables that best discriminate recidivists from non-recidivists during the greatest 'at risk' period and before other, longer-term processes emerge which might dilute the strength of key predictors.

Furthermore, this review aimed to provide a more nuanced analysis of the literature to explore both the limitations and potential of our current understanding of predictors of recidivism. To achieve this aim the study adopted a number of unique methodological approaches. First, only those prognostic studies meeting stringent quality criteria (Hayden et al., 2013) were selected for analysis. Second, we present the effect sizes for each factor according to how much variance the factor accounts for alone (bivariate analysis) in addition to how it performs in multiple regression models (multivariate). Third, based on Singh and colleagues (2014), the current meta-analysis also considered the impact of a number of methodological moderator variables on the predictive ability of these individual risk factors across varying samples and contexts.

Method

Selection of primary studies

Inclusion criteria

Studies had to meet four key criteria: a) they examined adults (age 18 and above) convicted and sentenced to custody; b) they followed up cases for a period of at least six months but no longer than four years whilst 'at risk' of recidivism in the community (i.e., released to a setting in which they had community access); c) they used objective measures of recidivism; and d) they reported effect sizes for individual predictors of recidivism. Six months was selected as the minimum time-frame to allow sufficient time for recidivism to be observed given the majority of recidivists are first arrested in the period between six months and one year after custodial release (Durose et al., 2014). Only those studies published in the last twenty years (1996 onwards) were included to ensure that the findings were generationally relevant. This meta-analysis was primarily interested in cohort, case control, and cross-sectional case studies.

Exclusion criteria

Studies that examined unconvicted detainees, young offenders (17 and younger), or those convicted and sentenced to community sentences only, were excluded. Also excluded were studies with follow-up periods shorter than six months or longer than four years (on average), and those published prior to 1996. The search terms also returned a number of studies primarily interested in the validation of risk assessment protocols. Such studies were excluded except where they reported the predictive accuracy of the individual predictors forming those risk assessments. Finally, any studies that were purely descriptive (i.e., reported incidence rates only), reported insufficient data on which to calculate an effect size, or separated the estimates by different groups or typologies (e.g., latent classes) were excluded from the analyses. Studies examining the effect of an intervention were not automatically excluded except where there was an unknown confounding effect of the intervention on the risk predictors being examined (i.e., post-intervention changes to risk predictors were not reported).

Definition of variables

Recidivism was operationally defined as any re-arrest, reconviction, re-imprisonment or parole revocation, including abscond. Given that some of these are more sensitive measures of recidivism than others, the intention was to present the results according to the four separate outcome measures. However, this separation had the effect of substantially diminishing the number of studies in which each predictor variable was tested and therefore reducing the power of the results. As such, the variables were pooled into a 'general recidivism' outcome measure. Recidivism/failure type was instead deployed as a potential moderator variable to account for any heterogeneity among effect sizes. Where studies presented multiple recidivism/failure outcome data, the results were selected according to the sensitivity of the recidivism/failure measure to increase the likelihood of 'capturing' recidivism outcomes. With the exception of parole revocation (which was the least preferred outcome measure), outcome data were preferred if they were more sensitive and less subject to system attrition, thus for example, re-arrest was selected ahead of reconviction.

A range of predictors were reported across the studies included. Predictors included personal variables related to the individual, including both static (e.g., age, criminal history, gender) and internal dynamic factors (e.g., aggression control, pro-criminal attitudes, impulsivity), and situational predictors related to the prison or community environments in which the offender resided (e.g., prison security level, residential stability, supervision intensity). Standardised assessments of clinical constructs were included (e.g., measures of aggression, impulsivity) and pooled together for the present meta-analysis. As mentioned earlier, standardised assessments of risk (i.e., actuarial or Structured Professional Judgment [SPJ] tools) were not included as predictors except where the predictive accuracy of individual risk factors specific to that tool were presented.

Search strategy

To perform a thorough search of the literature, this study adopted three search strategies. First, we undertook a thorough review of both the published and unpublished research literature, searching the abstracts of the following bibliographic databases relevant to the area of study: PsycINFO, Medline, Proquest, Web of Science, Opengrey, Cochrane library, C2-SPECTR, PSYNDEX, Criminal Justice Abstracts, UK Home Office database, Public Safety Canada database, and Google Scholar. The search procedure involved combining sets of search terms pertaining to three parameters i) risk predictors (Predict* OR Characteristic* OR Risk factor* or Risk marker*), ii) failure (Crime* OR Violen* OR Recidiv* OR Abscon* OR Escap* OR *Offen* OR Temporary release OR Temporary absence OR Breach*) and iii) post-release follow-up (Post-release OR Follow-up OR Discharge* OR Release*). All searches were completed in April 2017. Second, to locate additional relevant studies, we undertook a hand search of the references contained within the final set of included studies, as well as searching for studies citing those already retrieved. Finally, we contacted researchers internationally recognised in the field of recidivism risk predictors.

Coding procedures

A data extraction form was designed specifically to code the relevant data extracted from the studies. This included: (a) study descriptors (e.g., publication year, potential conflicts of interest), (b) a study eligibility screen, (c) context/setting descriptors (e.g., setting, population type), (d) method (e.g., design, follow-up duration), (e) sample descriptors (e.g., sample size, age, gender), (f) outcome measurement, (g) outcome data sufficient to calculate effect sizes, and (h) applicability to the research question.

The first author coded all studies in the meta-analysis. All the studies were rated independently by a postgraduate research assistant at the abstract screening phase. The 'hard-to-code' studies were rated independently by the second author at the final stage of assessing the quality of the studies.

Statistical methods

All but a few studies included in the meta-analysis used multiple regression models and presented summary data in the form of odds ratios (OR) and/or hazard ratios (HR). A smaller proportion of studies presented bivariate statistical data but typically presented these data for a smaller proportion of variables included in the final regression models. There is a long-standing debate about reporting multivariate effect sizes, with critics claiming they can be misleading (Aloe & Thompson, 2013) or fundamentally 'too different' to bivariate effect size estimates (Aloe, 2015; Siddaway et al., 2019). However, we adopted the position of Turanovic and Pratt (2020) to report separately multivariate effect size estimates alongside bivariate effect sizes estimates. Given that most studies report multivariate data this approach gives a truer reflection of the research literature. The multivariate data also act as a point of reference given bivariate effect sizes are often artificially inflated and liable to spurious findings when confounding effects have not been accounted for (cf. Ferguson, 2015). Although we had intended to convert the multivariate data into a common effect size measure, it was not possible to achieve this consistently given the limitations of the underpinning data presented across the studies. As such, the multivariate OR data have been retained and reported in the results, the multivariate HR data have been included as Supplemental Material (online version of manuscript), and the bivariate data have been converted to ORs and reported in the results.

ORs are best understood as the relative chance of the outcome given exposure to the variable of interest, using a defined endpoint (i.e., cumulative). An OR > 1.00 is associated with higher odds of the outcome and an OR< 1.00 is associated with lower odds of the outcome. For instance, if the OR for risk factor A is 1.60, there is a 60% increase in the odds of recidivism for a one-unit increase in the factor ((1.60-1) x 100). Conversely, if the OR for risk factor B is 0.74, there is a 26% decrease in the odds of recidivism ((0.74-1) x 100) for a one unit increase in the factor. The associated 95% confidence interval (CI) indicates the precision of the OR; a wide CI gives a low level of precision and a narrow CI indicates a higher level of precision. A 95% CI which overlaps the null value (i.e., 1.00) equates to a lack of reliable association between the exposure and outcome. As outlined in Chen, Cohen and Chen (2010), the relative magnitude of effect sizes is dependent on the disease rate or in this case, the base rate of recidivism. Given that the primary studies underpinning this meta-analysis report recidivism rates ranging between 10% and 78.2%, we opted to convert Cohen's (1988) rules of thumb to the corresponding odds values in Salgado (2018) and control for base rate variation in the moderator analyses. For the purposes of this meta-analysis, Cohen's *d* of .2 (small), .5 (medium) and .8 (large) are represented by ORs of 1.434, 2.488 and 4.258 respectively.

Both fixed effect and random-effects models were used. Random effects models are almost always conceptually superior in social sciences research (cf. Field, 2003; Hunter & Schmidt, 2000) because they assume that the true effect size varies randomly from study to study. Under this assumption, effect sizes should be heterogeneous as they come from populations with varying effect sizes (Field & Gillett, 2010). That is, there is a distribution of true effects and the summary effect is an estimate of the distribution's mean. In the random effects model, the between-study variability is included in the error term. Consequently, it is appropriate to generalise the findings beyond the studies included in the meta-analysis. However, when analyses include fewer than 30 studies, the precision of the between-study variability estimate (i.e., tau) deteriorates and greater weight should be given to fixed-effect models (Schulze, 2007). This was the case for all the predictors in this meta-analysis, hence we report both models to increase confidence in the results. Additionally, to determine consistency of effects across studies, only those effect size estimates based on samples of four or more studies are presented. Unfortunately, it was not possible to carry out moderator tests for several of our main analyses because of insufficient numbers of studies in each category.

Review Manager 5 (RevMan 5) software[1] was used with each effect size being weighted according to the inverse of its variance. This procedure is common in the wider meta-analysis literature (Fleiss & Berlin, 2009; Lipsey & Wilson, 2001). We also calculated the between-study variability using both the Q and I^2 index. The Q statistic tests for the existence of between-study variability and is presented as a chi-square with k-1 degrees of freedom. The I^2 index measures the size of the variability and is presented as a percentage. Together they describe the true heterogeneity among effect sizes rather than the error resulting from sampling variance. I^2 values of 25%, 50% and 75% may be considered as low, moderate, and large respectively (Higgins et al., 2003). Consistent with Hanson and Morton-Bourgon (2004; 2005) outliers were defined as any individual finding which was extreme (i.e., highest or lowest value), had a significant Q statistic, and the single finding accounted for more than 50% of the value of the Q statistic. Results containing an outlier are reported with and without the outliers.

Study selection

Figure 1 gives a visual appraisal of the study selection process. The search strategy resulted in a list of 1,123 relevant studies on the basis of their title and after removing duplicates. After reviewing abstracts, 371 were identified as potentially relevant and the full text of these articles were obtained. These studies were rated independently by the first author and a doctoral-level research assistant. There was a 19% disagreement rate. The inter-rater reliability was moderate (κ = 0.62). Any disagreements were resolved through discussion. After excluding those studies which met the exclusion criteria, 136 studies of varying quality remained. At this juncture, the 136 studies were subject to analysis using the Quality In Prognosis of Studies (QUIPS) tool (Hayden et al., 2013). QUIPS includes questions related to six areas considered important when evaluating validity and bias in studies of prognostic factors: participation (the study sample adequately represents the population of interest), attrition (there are no important differences between the study sample and those lost to follow up), prognostic factor measurement (prognostic factors are measured reliably and consistently), outcome measurement (the outcome measure is reliable and consistent), confounding variables (appropriately accounted for) and statistical analysis/reporting (the statistical analysis is appropriate and primary outcomes are reported). QUIPS inter-rater reliability varies between 0.56-0.82 (*Mdn* = 0.75). The first and second authors conducted the risk of bias analysis with independent agreement on all but 15 studies (κ = 0.75). Disagreement was resolved through discussion. Based on Higgins (2012), we removed all those studies presenting a high risk of bias (*n*=61) and discussed removal of any studies in which there was an unclear risk of bias in three or more areas (*n*=8). This resulted in 69 additional studies being excluded based on their risk of bias. The remaining 67 studies comprised the data-set for the present meta-analysis. Forty-three studies reported multivariate OR data and an overlapping set of 32 studies reported useable bivariate data. Thirty-two studies also presented HR data; related results are included in the Supplemental Material.

[Insert Figure 1 about here]

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[1] Review Manager (RevMan) is the software developed by Cochrane (British international medical research organisation) to support preparing, maintaining and analysing systematic reviews.

Results

Description of included studies

The current analysis produced in excess of 600 individual recidivism prediction effect sizes across 43 primary studies. The characteristics of the studies are presented in Table 1. The majority was conducted in the United States (74%), sourced from the published literature (81%) and published since 2012 (44%). Most studies reported on male samples (40%) or predominantly male samples (51%). The sample sizes of the studies ranged from 143 to 74,359 (*Mdn* = 951*, SD =* 10,766) with most studies measuring recidivism over 2-3 years. Re-arrest was the most frequent (40%) outcome measure.

[Insert Table 1 about here]

Effects for predicting recidivism – multivariate analyses

Those variables tested as predictors of recidivism in four or more studies in the multivariate analyses are presented in Table 2 in order of effect size (random effects), with those showing a direct relationship with risk for recidivism (i.e., OR>1.00) presented first followed by those showing an inverse relationship with risk for recidivism (i.e., OR<1.00). The results of the fixed effects and random effect analyses were broadly similar with the latter reported here unless stated. Sufficient data were available to draw conclusions about 20 factors. Ten of these increased the odds of recidivism with small effects, four decreased the odds of recidivism with small effects and six had no effect. The largest effect size was number of previous incarcerations with a 60% (OR = 1.60) increase in the odds of recidivism for each additional incarceration (including the outlier OR = 1.52, CI = 1.29, 1.80). The next largest were a range of indicators of a history of rule violation and criminality (ranging from OR = 1.48 for number of prior parole violations to OR = 1.05 for number of recent institutional infractions).

Prisoners of Black race had a 33% (OR = 1.33) increased odds of re-offending and based on the fixed effect analyses, was the strongest predictor of recidivism (OR = 1.44). However, the related data were based on US studies only and their generalisability to other jurisdictions should be interpreted with caution. Although not featuring in Table 2 because of a lack of power, it is noteworthy that being assessed as 'high risk' on a static risk assessment was the strongest predictor of recidivism, approaching a medium effect size (OR = 2.22, CI = 1.66, 2.98 after removing the outlier OR = 1.93, CI = 1.36, 2.75). This demonstrates the cumulative effect of combining multiple predictors of risk.

Four variables were associated with decreased odds of recidivism. These are presented in order of effect size in Table 2. Having an index offence of violence produced the largest effect size and was associated with a 26% (OR = 0.74) reduced odds of recidivism (including the outlier OR = 0.81, CI = 0.65, 1.01) compared to other offence types. The smallest effect size was for age with a 4% (OR = 0.96) decrease in the odds of recidivism for each additional year of age. One other variable, not presented in Table 2 which protected against recidivism was parole release (OR = 0.70, CI = 0.59, 0.82) but this was based on three studies only.

With the exception of time served in custody which showed no relationship with recidivism across any of the analyses, the utility of five variables in relation to risk prediction is unclear. Alcohol abuse did not predict recidivism except when including the outlier. Being employed at follow-up reduced the odds of recidivism in the fixed effect analyses but not in the random effects models except when including the outlier. Education level, Hispanic ethnicity, and intensity of community supervision showed no relationship with recidivism in the random effects analyses but decreased the odds of recidivism in the fixed effect analyses.

[Insert Table 2 about here]

Recidivism prediction moderator variables – multivariate analyses

Given the heterogeneity underpinning many of the effect sizes, it was possible that key methodological variables might influence the results. The following results, based upon a small number of comparisons suffer from low statistical power and should, therefore, be interpreted with the appropriate caution. Based on the findings of Singh et al. (2014), recidivism definition/measure, sample size, length of follow up, country of study, and the base rate of recidivism were used as moderator variables.

Significant results emerged in the moderator analyses for a handful of individual predictors only. None of the moderator variables consistently accounted for the heterogeneity observed and where heterogeneity was reduced, few clear patterns emerged from the data. For instance, 'prior criminal record' was moderated by sample size with higher ORs being reported with larger sample sizes. Sample sizes of 100-500 produced an overall OR of 1.01 whilst sample sizes of 5000+ had an average OR of 1.37. However, grouping the studies in this way reduced the heterogeneity in the 101-500 and 1001-5000 sample size groups but not the 501-1000 and 5001+ groups which remained significantly heterogeneous. In addition, race was moderated by follow-up time and base rate of re-offending ($Q = 12.20$, $p = .07$; $Q = 18.60$, $p<.00001$ respectively); with higher ORs observed with longer follow-up times (i.e., 0-1 year = 0.90; 1-2 years = 1.23; 2-3 years = 1.56) and higher base rates (i.e., <33% OR= 0.97, 33.1% - 56% OR= 1.35, >56.1% OR=1.67). Heterogeneity only remained significant in the longest follow up period and highest base rate groupings.

Effects for predicting time to recidivism

As shown in the Supplemental Material, sufficient data were available to draw conclusions about 14 variables, 13 of which featured in the recidivism analyses. Five factors increased the hazard of recidivism and three decreased the hazard of recidivism. The findings were consistent with the recidivism studies with small significant effects for number of previous incarcerations (HR = 1.61, including outliers, HR = 1.28, CI = 1.15, 1.42), Male gender (HR = 1.39) and having a property-related index offence (HR = 1.29) for example. The largest reduction in the hazard of recidivism was related to Parole release (HR = 0.50) which reduced the hazard by 50% but only after removing the outlier which rendered it non-significant (HR = 0.70; CI = 0.35, 1.40).

Effects for predicting recidivism – bivariate analyses

Those variables tested as predictors of recidivism in four or more studies in bivariate analyses are presented in Table 3. Sufficient data were available to draw conclusions about 17 factors. Ten of these predicted recidivism and are presented in Table 3 in order of effect size (random effects), with those showing a direct relationship with risk for recidivism (i.e., OR>1.00) presented first followed by those showing an inverse relationship with risk for recidivism (i.e., OR<1.00). The results are broadly similar to the multivariate analyses. The largest effect size with a small-medium effect (OR = 2.13) was number of previous incarcerations which evinced a 113% increase in the odds of recidivism for each additional incarceration (including the outlier OR = 2.45, CI = 1.63, 3.75). The smallest effect size was previous employment problems which was associated with a 26% (OR = 1.26) increase in the odds of recidivism. Employment problems did not feature in the multivariate analyses due to insufficient data. This was also true of criminal attitudes (OR = 1.52) and previous assaults/violence (OR = 1.45) which were significant predictors in the bivariate analyses. Parole violations, a history of mental illness, and a prior criminal record – predictors in the multivariate analyses, did not feature in a sufficient number of bivariate analyses.

Five variables were associated with decreased odds of recidivism. These are presented in order of effect size in Table 3. Completion of structured programmes to address risk produced the largest effect size and was associated with a 40% (OR = 0.60) reduced odds of recidivism although the result was no longer significant when including the outlier (OR = 0.73, CI = 0.51, 1.06). The smallest effect size was for having a violent index offence conviction. The odds of recidivism in this group were reduced by 8% (OR = 0.92) compared to other offence types. Being married (OR = 0.70) was a protective factor which was not reported in sufficient numbers on the multivariate analyses. Conversely, being employed prior to custody and having a drug-related index offence were associated with decreased recidivism in the multivariate analyses but did not feature in sufficient studies in the bivariate analyses.

Like the multivariate analyses, time served showed no relationship with recidivism whilst educational level did so in the fixed effect analyses only (OR = 0.93, CI = 0.89, 0.98). Alcohol abuse, Hispanic ethnicity, intensity of community supervision and being employed at follow-up – all non-significant in the multivariate analyses did not feature in sufficient numbers of bivariate analyses to draw conclusions about their predictive ability.

Recidivism prediction moderator variables – bivariate analyses

Once more, a small number of significant results emerged in the moderator analyses for a handful of predictors only. Gender was moderated by recidivism/failure outcome type (Q = 16.30, p = 0.001) and follow up (Q = 13.93, p = 0.003) but there was no significant reduction in heterogeneity or patterns amongst the moderator variables. Similarly age at release was moderated by country of study origin (Q = 20.60, p = 0.0001) and sample size (Q = 13.69, p = 0.001). Neither moderator variable reduced the heterogeneity albeit a pattern emerged with respect to sample size with greater effect sizes being observed for age at release in small samples (0-500 = 0.48, 501-1000 = 0.52, and 1001-5000 = 0.78). Finally, substance misuse was moderated by follow up time (Q = 20.20, p =0.0002), recidivism/failure outcome type (Q = 13.07, p = 0.004) and country of study origin (Q = 38.65, p <0.00001). Of note, effect sizes were higher for substance misuse in the reconviction (2.20) outcome group and lowest for the rearrest (1.23) outcome group. Likewise, substance misuse had a larger impact in Canadian study samples (3.32) compared to the European (1.92) and US (1.13) studies. These findings were consistent across the Canadian and US samples (i.e., heterogeneity was no longer significant) but not the European studies where the effect sizes were more variable across studies.

Discussion

Predictors of recidivism

The primary aim of the present study was to explore the current state of the recidivism prediction literature and specifically, to identify which risk indicators or factors are best at predicting recidivism across heterogeneous samples, following custodial release. Distinguishing, at custodial release, single episode offenders from those likely to persist in their criminal behaviour, is critical so that criminal justice professionals can target resources effectively to reduce the risk of harm to the public.

The current meta-analysis identified 17 factors which were associated with increased or decreased risk of recidivism across the bivariate and multivariate analyses. Consistent with Bonta and Andrews' (2017) General Personality and Cognitive Social Learning (GPCSL) theory that there are essentially a 'central eight' risk factors for recidivism, the majority of factors identified in this study could be accounted for within the four domains of antisocial potential ('big four'): History of Criminal Behaviour; Antisocial Personality Pattern, Antisocial Cognitions, Antisocial Companions (Andrews et al., 2006). Consistently shown to be associated with an increased risk of recidivism in this meta-analysis for instance were: Number of prior incarcerations, convictions, and arrests; having a prior criminal record; and having pro-criminal attitudes. These findings broadly corroborate the findings of previous meta-analyses which demonstrate that these domains have the strongest associations with general recidivism (Eisenberg et al., 2019; Gendreau et al. 1996; Katsiyannis et al., 2018).

In addition to this, a number of other factors, which can perhaps be more readily described as risk markers or indicators of the 'big four' risk factors, also predicted recidivism. Thus violations of parole and institutional infractions might be markers of an antisocial personality or antisocial orientation for instance. Likewise, those with a property-related index offence have a higher odds of recidivism compared to those with drugs or violent (including sexual) offences; the acquisitive offence-type perhaps being an indicator for a particular type of criminal mind-set/lifestyle. Indeed, Travers et al. (2014) found that property offenders tended to be resistant to cognitive skills programmes and may be more greatly represented by a sub-group of 'career criminals' who are not deterred by custody and in some cases, view it as a 'badge of honour' (Crank & Brezina, 2013; Sampson & Laub, 2003). The prolificacy of property offenders may also be intuitively explained by opportunity; they are generally subject to shorter sentences and are younger at release therefore, compared to those convicted of violent offences for instance (Spivak & Damphousse, 2006). Indeed, age reduced the odds of recidivism in this study with older offenders perhaps having had greater opportunity to mature and desist from their criminal lifestyles (Sampson & Laub, 2003).

Three of the remaining four risk factors for recidivism were also represented in the results but broadly, as per the GPCSL theory (cf. Bonta & Andrews, 2017) had smaller associations with recidivism. That is, drug abuse (Substance Abuse) and employment problems (School/Work) increased the odds of recidivism whilst marriage reduced the risk (Family/Marital). Whilst drug abuse had a comparatively strong association with recidivism compared to other variables in the bivariate analyses, the effect was diluted in the multivariate analyses. It is possible therefore that drug abuse is often representative of a wider pattern of antisocial behaviour (cf. Moffitt, 1993) and it is these markers of antisociality which more reliably predict recidivism.

Two other variables had associations with recidivism which are given less salience in GPCSL theory but are nonetheless supported in the recidivism literature (Eisenberg et al., 2019; Gendreau et al., 1996; Katsiyannis et al., 2018). First, being male increased the odds of recidivism. Moffitt and colleagues (2001) found that males are 10-15 times more likely to follow a life-course persistent pattern of offending compared to females, largely the result of biopsychosocial interactions found more commonly in male children (Moffitt, 1994). Second, participating in structured programmes designed to address risk factors lowered the odds of recidivism. Whilst this finding is at odds with one recent large scale single-study (cf. Mews et al., 2017), more recent meta-analyses have demonstrated the consistency of this effect, particularly in interventions that adhere to the Risk Need Responsivity (RNR) model (Gannon et al., 2019).

Two factors in this meta-analysis showed associations with recidivism which are not roundly accepted as risk factors in the general recidivism literature. The first is history of mental illness, which emerged as a risk factor in the multivariate analyses. The bivariate meta-analyses of Eisenberg et al. (2019), Gendreau et al. (1996) and Katsiyannis et al. (2018), found no such association. It is possible therefore that mental illness has a mediating effect on risk; good mental health is protective but mental illness provides no such protection when risk factors for antisocial propensity are present. Alternatively, some forms of mental illness such as schizophrenia have been found to have greater associations with recidivism (cf. Gottfried & Christopher, 2017) so it is possible that there was a greater representation of these illnesses in the primary studies in this meta-analysis. Race, was also consistently associated with increased odds of recidivism in the bivariate and multivariate analyses, with a positive association between Black race and increased odds of recidivism. However, this finding was based on a group of 12 studies, all of which were conducted in the USA. Institutional racism in the law enforcement and judicial systems in the USA is one often cited explanation, but Reisig and colleagues (2007) say this is too simplistic. They suggest that such findings should be understood in the context of racial inequality. They found that Black offenders were at increased risk of recidivism when returning to communities where there were larger disparities between Black and White constituents in income, joblessness, and poverty. Thus if being of Black race confers greater exposure to disadvantage and other inequalities, the opportunities to desist in these communities might be fewer (cf. Glynn, 2013).

Factors with little or no association to recidivism

The meta-analysis identified one factor which had little or no association with recidivism: percentage of custodial time served. Whilst longer prison stays inevitably result in offenders leaving prison at an older age (associated with desistance), time served in itself is not an accurate measure of whether an individual has been rehabilitated and will be successful on re-entry into the community. Meade and colleagues (2013) found that only those serving the longest sentences had lower odds of recidivism and this was not realised until offenders had served at least five years. Visher and Travers (2003) also suggest that long prison sentences may alienate some individuals from mainstream society and make successful reintegration harder to achieve thus moderating the effects of age.

This meta-analysis was unable to support the clinical utility of alcohol abuse, education level and intensity of supervised release as predictors of recidivism. First, alcohol abuse did not show an association with recidivism except when an outlier study was included in the analysis. This finding is generally inconsistent with previous studies which separate alcohol and substance abuse (Dowden & Brown, 2002; Boden et al., 2013). The contrasting findings may lie in the demographics of the sample. Alcohol misuse has been shown to have the strongest relationship with violent offences which are impulsive or follow a dispute (Boden et al., 2013; Felson & Staff, 2010). Given the recidivists in this study were more likely to be property offenders (58% increase in the odds of recidivism) compared to violent offenders (8% decrease in the odds of recidivism), it is possible that fewer instances of alcohol misuse in relation to recidivism are reported. Whilst this study does not support the clinical utility of alcohol abuse as a predictor of general recidivism, the evidence here is insufficient to conclude that it is not associated with recidivism. Education level and intensity of supervised release showed associations with recidivism in the fixed effects analyses but not the random effects analyses. They do not feature as predictors of recidivism in recent past meta-analyses (Eisenberg et al. 2019; Gendreau et al. 1996; Katsiyannis et al., 2018). Indeed, as concepts they may be too simple to predict risk. For instance, Duwe and Clark (2000) suggest that the association between education and criminal behaviour is likely moderated by a number of situational risk factors on re-entry into the community such as post-release employment opportunities. That is, education level is a poor measure of securing work and of the protection against crime afforded by employment. Likewise, intensive supervision perhaps provides the necessary accountability and support for those who are motivated to desist but ensnares those who disengage and persistently engage in risky behaviours (cf. Farrall, 2002). Intensive supervision therefore may only ever be a necessary mechanism for the protection of the public rather than protecting against recidivism. Nonetheless, Drake (2011) notes that the nature and overarching approach to supervision (i.e., surveillance versus rehabilitation) by the supervising officer might affect outcomes and on that basis, it cannot be ruled out as conferring a protective effect if delivered using principles of effective rehabilitation/intervention (Bonta & Andrews, 2017).

Moderator variables

The current meta-analysis isolated a number of factors that are related to recidivism and these associations are apparent across samples in various jurisdictions, using multiple outcome measures and follow-up times. Not surprisingly, there was substantial heterogeneity in the results. Singh et al. (2014) outline the impact that such heterogeneity has on the accuracy of risk assessments. We therefore tested whether isolating key moderator variables such as base rate of re-offending, country of study origin, follow-up time, recidivism outcome measure, and sample size, could reduce variability by suggesting how to weight individual predictors based on the moderators present.

The base rate of re-offending and follow-up time showed the most promise at reducing heterogeneity in the effect sizes. However, they only reduced the heterogeneity in a handful of risk factors. Even then, it was not always possible to identify patterns in the predictive ability of the factors according to the sub-group analyses. Meta-analyses of risk prediction tools have similarly failed to successfully reduce the level of heterogeneity using similar moderator variables (Campbell et al., 2009). We posit that the interplay between moderator variables and individual risk predictors is complex and we conclude that trying to find patterns in the data is likely futile. The primary means of mitigating heterogeneity in risk prediction then is to develop and amend risk protocols according to the samples and jurisdictions in which they will be used. If professionals do apply to a new population those risk assessments tools constructed on a different population, they should at least be cognisant of the different samples and base rates of re-offending in the present/cross-validation and previous/construction samples and the associated issues and limitations (Mossman, 2006).

Implications for practice

Drawing on a large body of multivariate studies and supported by studies of bivariate effects, this meta-analysis presents a set of factors predictive of recidivism, consistent with previous recidivism meta-analyses (Eisenberg et al. 2019; Gendreau et al. 1996; Katsiyannis et al., 2018). These risk predictors are consistent across heterogeneous samples and support existing theories about the characteristics of those who persist in their offending behaviour (Moffitt, 1993). These factors were primarily static in nature and support the superior prediction of static over dynamic factors (Caudy et al., 2013; Coid et al., 2009; Morgan et al., 2013). Yet this conclusion should be understood in the context of the limitations of the risk prediction literature.

First, from a pool of over 600 individual effect sizes, taken from the highest quality studies, and after removing outliers, only 21 potential risk predictors were studied four or more times and could be used in the data analysis. There were a number of potentially promising risk predictors based on one or two studies but without further evidence it is difficult to draw reliable conclusions about their relationship with recidivism. Of those 21 potential risk predictors, all but two were static in nature. No one situational risk factor featured in four or more studies. Indeed, the majority of the eligible studies and those which formed the meta-analysis were retrospective in nature where data pertaining to static factors is more readily defined and accessible (Lehmann et al., 2016). Where dynamic/changeable risk factors were measured in more than one study, there was often variability in the definition of the risk factor, or indeed, variability in the type of data that were collected as evidence for the risk factor. For instance, impulsivity was measured using self-report studies, behavioural observations and 'go-no go' tasks making it difficult to conclude that they are measuring the same construct. Indeed, almost one-half of the eligible studies investigating individual predictors of recidivism over the past 20 years were of insufficient quality to be included in this meta-analysis with prognostic factor measurement undermining the quality assessment of several of those papers. We assert that if, conceptually, static and dynamic risk factors are independent entities, the former will remain superior as a predictor of recidivism given the problems with defining and measuring dynamic risk factors (Heffernan et al., 2019). Good quality prospective studies, exploring the predictive accuracy of clearly defined dynamic or changeable variables is required. Until then, in the field of recidivism risk prediction at least, there is as yet no evidence that they are better risk predictors compared to static factors (Casey, 2016; Harris & Rice, 2015; Heffernan et al., 2019).

In addition to clearly defining dynamic risk factors, such risk factors should be measured more than once and the predictive ability of the post-intervention score should exceed rather than supplement the predictive ability of the pre-intervention score to reliably conclude that it is the change in the risk factor which predicts recidivism (Harris & Rice, 2015). Consistent with the findings of Eisenberg and colleagues (2019), many of the papers reporting on dynamic risk predictors in this meta-analysis had measured at a single time point and were arguably therefore, measuring and describing a historic or 'static' concept. The risk prediction literature is dominated by studies of static variables personal to the individual (e.g., age, previous convictions) and internal dynamic risk factors (e.g., criminal attitudes, impulsivity) measured at single time points. Situational risk factors were represented to a lesser degree and there was a virtual absence of high quality studies assessing the link between endocrinal, (epi-)genetic, or motivational systems and offending for instance (cf. Kruger & Kneer, 2021; Ward & Carter, 2019). Further research is required into such risk factors. We propose the use of behavioural monitoring as a preferred means of tracking meaningful/reliable changes over time (Clark et al., 1993; Jones, 2004; McDougall et al., 2013; Pearson & McDougall, 2017) given the need for a focus on objective (behavioural) rather than subjective (cf. Tan & Grace, 2008; Tierney & McCabe, 2001) indicators of change and longitudinal over cross-sectional risk assessment (Large & Nielssen, 2017). Behavioural monitoring also affords the opportunity to tap into 'low-level' behaviours indicative of antisocial persistence, the interplay between situational determinants of recidivism on dynamic risk factors and in identifying the presence of 'new' behaviours, not typically associated recidivism.

Conclusions

The current findings add further weight to the view that measures or markers of an antisocial lifestyle are the strongest known predictors of recidivism (Eisenberg et al. 2019; Gendreau et al. 1996; Katsiyannis et al., 2018; Moffitt, 1993). Previous incarcerations, convictions and arrests; being male, having committed a property-related index offence, a history of substance misuse, previous employment problems, holding pro-criminal attitudes and committing prison infractions all showed statistically significant relationships with recidivism. Older age and completing structured offence-focussed treatment reduced the risk of recidivism. All factors showed a small effect on recidivism. Yet the risk factor literature is skewed towards retrospective studies of risk factors which are largely static in nature. The identification of reliable dynamic predictors of recidivism are beset by issues of quality, primarily relating to their consistent definition and measurement, thus restricting their predictive capacity (Casey, 2016; Harris & Rice, 2015; Heffernan et al., 2019). Rectifying these conceptual issues, measuring the 'change' information and using objective behavioural indicators are potential means of unlocking the promise of dynamic risk factors. Behavioural analysis of high risk situations also has potential for identifying risk relevant constructs/factors.

The data that support the findings of this study are available from the corresponding author, [GG], upon reasonable request.

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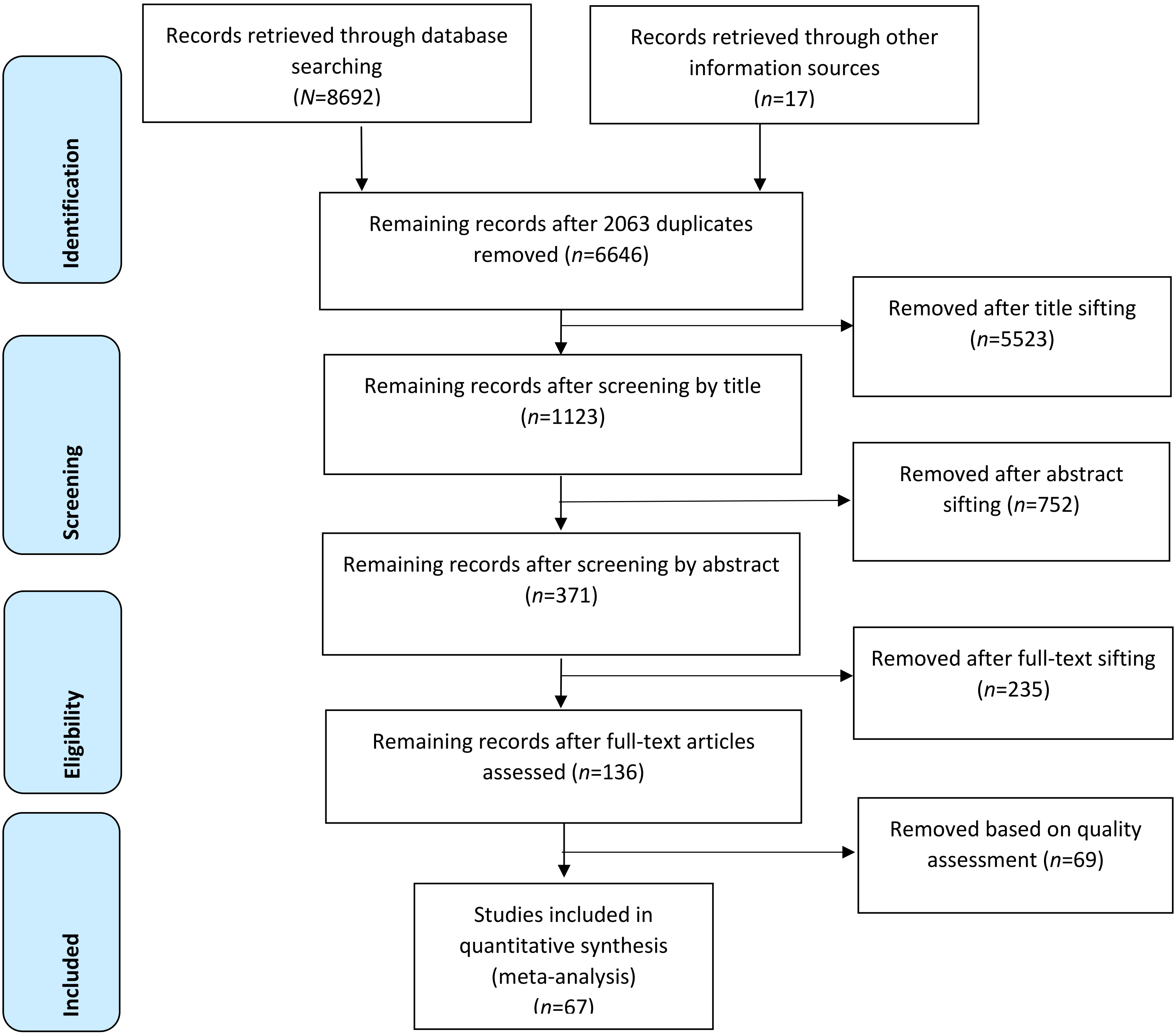
Figures

1. PRISMA diagram for the selection of studies for the present meta-analysis.



Tables

Table 1. Characteristics of Studies (n=67) Included in the Meta-Analysis

Variable	**Frequency (percent) (k = 43)**
Publication source	
Published	35 (81.4%)
Unpublished	8 (18.6%)
Country	
United States	32 (74.4%)
United Kingdom	5 (11.6%)
Canada	3 (7.0%)
Sweden	2 (4.7%)
New Zealand	1 (2.3%)
Gender	
Male	17 (39.5%)
Female	4 (9.3%)
Both	22 (51.2%)
Year of publication	
1996-2003	9 (20.9%)
2004-2011	15 (34.9%)
2012-2017	19 (44.2%)
Sample sizes	
100-500	15 (34.9%)
501-1000	8 (18.6%)
1001-5000	11 (25.6%)
5001-10000	4 (9.3%)
10001-50000	4 (9.3%)
50001-100,000	1 (2.3%)
Follow up period (months)	
6-12	12 (27.9%)

13-24	13 (30.2%)
25-36	14 (32.6%)
37-48	4 (9.3%)
Recidivism outcome variable	
Rearrest	17 (39.5%)
Reconviction	15 (34.9%)
Reincarceration	6 (14.0%)
Parole revocation	2 (4.7%)
Any recidivism	3 (7.0%)

Note. k= number of samples included in the analysis

Table 2. Predictors of Recidivism – multivariate analyses

			Random effects		Fixed effects			
Predictor	*k*	*Ni*	OR_w	95% CI	OR_w	95% CI	*Q*	I^2
Possible risk factors								
Number of previous incarcerations[a]	10	46820	1.60***	[1.36, 1.89]	1.37***	[1.30, 1.44]	61.21***	85.0
With outlier	11	101101	1.52***	[1.29, 1.80]	1.07***	[1.05, 1.09]	166.29***	94.0
Previous Parole Violation (yes=1, no=2)	9	70430	1.48***	[1.18, 1.91]	1.37***	[1.33, 1.41]	365.83***	98.0
Gender (male=1, female=0)	15	129880	1.47***	[1.31, 1.65]	1.41***	[1.32, 1.51]	27.64*	49.0
Index offence (property)[a]	5	43968	1.36***	[1.24, 1.50]	1.35***	[1.27, 1.44]	6.32	37.0
With outlier	6	48665	1.31***	[1.16, 1.48]	1.32***	[1.24, 1.40]	13.19*	62.0
Race (black=1, white=0)	12	132664	1.33***	[1.19, 1.49]	1.44***	[1.37, 1.49]	42.52***	74.0
Drug abuse (present=1, absent=0)	14	38520	1.31***	[1.15, 1.50]	1.13***	[1.10, 1.17]	114.54***	89.0

Number of previous arrests[a]	6	46442	1.18***	[1.09, 1.28]	1.09***	[1.08, 1.10]	18.21**	73.0
With outlier	7	51951	1.12***	[1.06, 1.18]	1.02***	[1.02, 1.02]	149.89***	96.0
History of mental illness (yes=1, no=0)	5	38753	1.12***	[1.05, 1.21]	1.12***	[1.05, 1.20]	3.04	0.00
Prior criminal record (yes=1, no=0)	15	12377	1.12***	[1.08, 1.16]	1.04***	[1.04, 1.05]	227.23***	94.0
Number of institutional infractions[a]	4	24419	1.05†	[1.00, 1.10]	1.02†	[1.02, 1.02]	8.99*	67.0
With outlier	5	50953	1.02***	[1.01, 1.03]	1.02***	[1.02, 1.02]	152.97***	97.0
Age at release	27	157792	0.96***	[0.95, 0.97]	0.97***	[0.97, 0.97]	1572.66***	98.0
Index offence: Drugs	9	85056	0.86***	[0.75, 0.98]	0.83***	[0.79, 0.88]	28.47***	72.0
Employed prior to custody (yes=1, no=0)	4	14708	0.84***	[0.78, 0.91]	0.84***	[0.78, 0.91]	1.53	0.00
Index offence: Violence[a]	4	49332	0.74***	[0.67, 0.83]	0.74***	[0.67, 0.83]	1.25	0.00
With outlier	5	51595	0.83†	[0.65, 1.01]	0.83***	[0.75, 0.91]	14.98**	73.0
				Potentially misleading risk factors				
History of alcohol abuse[a] (yes=1; no=0)	4	17303	1.10	[0.98, 1.23]	1.05†	[1.00, 1.09]	5.62	47.0
With outlier	5	17873	1.25†	[1.03, 1.50]	1.06***	[1.02, 1.11]	19.47***	79.0
Time served	10	81520	1.00	[0.99, 1.00]	1.00***	[0.99, 1.00]	68.78***	87.0
Education level[b] (high school qualification=1; none=0)	6	73493	0.93	[0.82, 1.06]	0.95***	[0.95, 0.95]	9.02	45.0
With outliers	8	86957	0.88	[0.60, 1.29]	0.95***	[0.95, 0.95]	466.42***	98.0
Ethnicity: Hispanic[a] (Hispanic=1; White =0)	5	66036	0.93	[0.78, 1.11]	0.86***	[0.80, 0.92]	8.89	55.0
With outlier	6	92570	0.86	[0.66, 1.12]	0.76***	[0.72, 0.81]	54.82***	91.0
Intensive community supervision (yes=1; no=0)	5	101748	0.85	[0.55, 1.30]	0.63***	[0.60, 0.67]	76.16***	95.0
Employed at follow up[a] (yes=1; no=0)	7	5815	0.75	[0.53, 1.06]	0.72***	[0.66, 0.80]	56.45***	89.0
With outlier	8	7030	0.64	[0.42, 0.97]	0.64***	[0.59, 0.71]	114.23***	94.0

Note. k = number of studies included in the analysis; N_i = number of prisoners included in the sample; ORw = mean weighted odds ratio; CI = confidence interval of ORw ; Q = test of homogeneity of effect sizes; I^2 = proportion of dispersion due to variability between studies.

The reference group for index offence was 'other offences' which included any offence which did not fall under the following categories: violent, sexual, drug, property, robbery, fraud, criminal damage or theft offences.

[a] One outlier removed

[b] Two outliers removed

†$p<0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$

Table 3. Predictors of Recidivism – bivariate analyses

			Random effects		Fixed effects			
Predictor	***k***	***N_i***	**OR_w**	**95% CI**	**OR_w**	**95% CI**	**Q**	**I^2**
Possible risk factors								

Number of previous incarcerations[a]	5	4768	2.13***	[1.61, 2.81]	2.15***	[1.93, 2.41]	22.40***	82.0
With outliers	6	8035	2.47***	[1.63, 3.75]	2.81***	[2.56, 3.08]	93.13***	95.0
Drug abuse (present=1, absent=0)	13	13588	1.75***	[1.30, 2.38]	1.93***	[1.80, 2.07]	187.37***	94.0
Index offence: Property	5	10430	1.58***	[1.32, 1.90]	1.64***	[1.48, 1.81]	8.97†	55.0
Number of previous convictions	6	7207	1.54***	[1.08, 2.18]	1.36***	[1.27, 1.45]	48.66***	90.0
Criminal attitudes[a]	5	3083	1.52***	[1.33, 1.73]	1.52***	[1.33, 1.73]	2.54	0.0
With outlier	6	3242	1.67***	[1.33, 2.08]	1.59***	[1.40, 1.80]	12.22**	59.0
Number of institutional infractions	4	1987	1.45***	[1.17, 1.80]	1.45***	[1.17, 1.80]	1.95	0.0
Previous assault/violence[a] (yes=1; no=0)	4	7183	1.45***	[1.33, 1.58]	1.45***	[1.33, 1.58]	2.73	0.0
With outlier	5	7482	1.35***	[1.16, 1.57]	1.42***	[1.31, 1.54]	10.63**	62.0
Race (Black=1, White=0)	12	15428	1.40***	[1.25, 1.56]	1.49***	[1.39, 1.59]	18.08†	39.0
Gender (male=1, female=2	12	75547	1.39***	[1.21, 1.58]	1.25***	[1.21, 1.29]	93.84***	88.0
Employment problems (yes=1, no=0)	4	2476	1.26***	[1.09, 1.45]	1.26***	[1.09, 1.45]	0.75	0.0
Offence type: Violence[c]	6	5132	0.92**	[0.86, 0.97]	0.92**	[0.86, 0.97]	4.01	0.0
With outliers	9	12948	0.71	[0.45, 1.13]	0.76***	[0.72, 0.80]	402.96***	98.0
Marital status (married=1, single=0)[a]	9	8361	0.70***	[0.62, 0.80]	0.73***	[0.67, 0.79]	13.47	41.0
With outlier	10	9991	0.73***	[0.61, 0.86]	0.88***	[0.83, 0.92]	45.74	80.0
Age at release	19	23411	0.62***	[0.53, 0.73]	0.99***	[0.99, 0.99];	252.37	93.0
Completion of a structured programme to address risk factors[a] (yes=1; no=0)	4	11972	0.60***	[0.45, 0.80]	0.68***	[0.62, 0.73]	16.49	82.0
With outlier	5	12707	0.73	[0.51, 1.06]	0.70	[0.65, 0.75]	40.45***	0.90
Potentially misleading risk factors								
Education level[a] (High school qualification=1; none=0)	8	5305	0.88	[0.76, 1.01]	0.93**	[0.89, 0.98]	13.05	46.0
With outlier	9	5875	0.98	[0.75, 1.28]	0.96	[0.92, 1.01]	70.53***	89.0
Time served	7	10443	0.83	[0.64, 1.07]	1.00	[0.99, 1.00]	70.28***	91.0

Note. k = number of studies included in the analysis; N_i = number of prisoners included in the sample; ORw = mean weighted odds ratio; CI = confidence interval of ORw ; Q = test of homogeneity of effect sizes; I^2 = proportion of dispersion due to variability between studies.

The reference group for index offence was 'other offences' which included any offence which did not fall under the following categories: violent, sexual, drug, property, robbery, fraud, criminal damage or theft offences.

[a] One sample removed from analysis (outlier)

[b] Two samples removed from analysis (outliers)

[c] Three samples removed from analysis (outliers)

†$p<0.1$, *$p < 0.05$, **$p < 0.01$, ***$p < 0.001$