Targeting and Evaluating a Behavioural Monitoring Process Designed to Improve the Risk Management of Prisoners in the Open Prison Estate

By

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Abstract

Open prisons play a unique role in the preparedness and resettlement of prisoners nearing the end of their sentences such that graduated exposure to the community has been associated with lower recidivism rates. Yet the nature of these institutions increases the hazard that harmful behaviours spill out into the community. In 2014, prisons in England and Wales adopted the Enhanced Behaviour Monitoring framework to provide assurances that the risks - of abscond, recidivism, and temporary release failure - were managed. The purpose of this thesis was to evaluate the impact of Enhanced Behaviour Monitoring on the rate of failures in open prisons.

To achieve this aim, Study 1 employed meta-analysis to identify risk factors associated with failure in the immediate years following release from custody (i.e., exposure to the community). Study 2 utilised these variables to build a model upon which to predict ‘failure’ in open conditions. Study 3 was an evaluation of Enhanced Behaviour Monitoring to compare the failure outcomes of those allocated to the intervention with a control group matched on the variables associated with failure identified in Study 2.

Seventeen risk factors for recidivism were identified, six of which were associated with recall from open to closed conditions. Indeed, these recall rates were disproportionate to the rate of serious recidivistic outcomes such as abscond, and both custodial and community re-offending, which were rare. Enhanced Behaviour Monitoring had a null effect on reducing failures; those allocated to Enhanced Behaviour Monitoring were overall at higher risk of recall to closed conditions.

This thesis contributes to the literature by advocating for longitudinal, individualised assessments of risk in open prisons, based on behavioural aggregation, to inform community risk management plans. Effective risk management in open
conditions is best achieved through procedural change and cultural enhancement, rather than scrutiny of individual-level risk factors.
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Declaration

Whilst registered as a candidate for the above degree, I have not been registered for any other research award. The results and conclusions embodied in this thesis are the work of the named candidate and have not been submitted for any other academic award.

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<td>CI</td>
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<td>EBM</td>
<td>Enhanced Behaviour Monitoring</td>
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<td>HMPPS</td>
<td>Her Majesty’s Prison and Probation Service</td>
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<td>HR</td>
<td>Hazard Ratio</td>
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<td>ISP</td>
<td>Intensive Supervision Programme</td>
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<td>GPCSL</td>
<td>General Personality and Cognitive Social Learning</td>
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<td>QUIPS</td>
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<td>RoTL</td>
<td>Release on Temporary Licence</td>
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<td>SoS</td>
<td>Secretary of State</td>
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<td>SPJ</td>
<td>Structured Professional Judgement</td>
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<td>TR</td>
<td>Treatment Received</td>
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Dissemination

Articles


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Chapter 1: Introduction

1.1. The Purpose and Benefit of Open Prisons

In England and Wales, the location of the current studies, the purpose of prisons has changed over time: evolving from an alternative to both corporal and capital punishments in the eighteenth century (Howard League, 2016) to their current function. Today’s prisons aspire to reform – by supporting offenders to lead law-abiding and useful lives – whilst simultaneously maintaining the highest levels of public protection (HMPPS, 2017). That evolution has been underpinned by a rich history of penal reform, none more progressive, arguably, than the advent of open prisons. Open prisons are facilities which typically have no perimeter security. Compared to a closed prison, there are fewer physical (e.g., gates, locks, fences) and procedural (e.g., rules, regulations) controls. Those residing there are trusted to complete the final years of their, often lengthy, sentences with minimum supervision and limited restrictions on their activity and movement.

The first adult male open prison in England and Wales, New Hall Camp, was commissioned in 1933 – a potential solution for improving access to employment following long-term incarceration (Smith, 2018). Encapsulating the dilemma facing the Prison Service, Sir Alex Paterson, a prominent penal reformer of the time said: ‘You cannot train a man for freedom under conditions of captivity’ (Howard League, 2016, para. 21). Radically, New Hall Camp was not only populated with those serving shorter sentences for relatively minor offences but also with those having committed more serious crimes who were nearing the end of their sentence (Smith, 2018). Leitch (1951, p. 26) in his commentary on the selection of men for open prisons, explains the inherent challenge:
the easy way would have been to have searched the men’s records for evidence of mental instability, immorality, violence, and general lawlessness, picked out the bad ones, and them labelled them as permanently unsuitable [for open prison]... the promising material remaining would have been allocated [to open prison] with a strong probability that the outcome would be successful. Of what value would such a prison be? These cases would in any case almost certainly have been successes on their return to civil life.

Ostensibly, the open prison experiment was considered a success. In England and Wales there now exist thirteen open prisons for adult male prisoners nearing the end of their sentence (Ministry of Justice, 2022a), playing a unique role in the rehabilitation, preparedness, and resettlement of those prisoners.

1.2. How Open Prisons May Mitigate Recidivism Risk

Notwithstanding their 90-year history, there exists no empirical or systematic evaluation of the impact of open prisons on recidivism in England and Wales. The community recidivism rates of those released from open prisons in England and Wales – approximately ten per cent (Ministry of Justice, 2019a), is substantially lower than the average community recidivism rate of all prisoners released from custodial sentences of twelve months or more – approximately 23% (Ministry of Justice, 2022b). However, these recidivism rates are irrefutably skewed, to some degree at least, as a function of selection bias. That is, open prison placement is conferred upon those satisfying a defined selection criterion, heavily predicated on the extent to which the
risk to the public is mitigated (Ministry of Justice, 2020a). Resultingly, this sub-group of prisoners is unrepresentative of the wider prison population.

To date, internationally, there has been just one attempt to evaluate the true impact of open prisons on recidivism rates (Mastrobuoni & Terlizzese, 2022). To overcome the problem of selection bias, Mastrobuoni and Terlizzese (2022) analysed the recidivism outcomes of a subset of prisoners displaced to Bollate open prison in Italy, due to overcrowding in the nearby feeder prisons. These prisoners were not required to meet the standard selection criteria of the prison. Whilst the researchers were unable to determine the extent to which the displacement mechanism was random, their analyses did control for several confounding factors known to impact on recidivism rates. Mastrobuoni and Terlizzese (2022) found that switching to an open prison regime for one-year reduced recidivism by six percentage points, against an average three-year recidivism rate of 40%. That is, ‘spending more time in an open prison, and correspondingly less time in one of the other traditional, closed prisons, reduces recidivism by a statistically significant and economically meaningful amount’ (p. 31). Whilst it was beyond the scope of their study to pinpoint the underlying causal mechanism for this six-percentage point reduction, the researchers hypothesised that multifarious factors were responsible, namely: greater freedom; increased responsibilities; and access to rehabilitation opportunities – particularly in the form of work placements.

Reasons exist to believe that the features of, and service provisions within, open prisons – not easily replicated in closed prisons – also impact positively on community recidivism rates. One such feature is the social climate of the prison. Although there is no universally accepted definition of social climate, most authors agree that it is a multi-dimensional construct based on the residents’ perception of
their safety from physical threat, the degree to which their physical/psychological needs are met, the provision of opportunities for personal development, and the extent to which prison is experienced as dehumanising (Auty & Liebling, 2020; Tonkin, 2015). The latter is dependent on the extent to which the prison is experienced as decent, fair, and operated by competent staff who utilise their authority legitimately (Liebling, 2011). In an analysis of 24,508 surveys Measuring Quality of Prisoner Life (MQPL) across England and Wales between April 2009 and December 2013, Auty and Liebling (2020) found that those prisons scoring higher on a number of dimensions of social climate, in particular decency, safety, and well being, had lower proven re-offending rates. Whilst open prisons are not assured of these features, their characteristic and purpose give them an advantage (cf. Andvig et al., 2021). Again Leitch (1951, p. 31) helpfully surmises:

the increase in freedom and amenities act as a stimulus to good conduct as they [the prisoners] feel that they have so much to lose by misbehaviour. Moreover, that intangible something we call 'atmosphere' has its effect. For example, the topics of conversation among the prisoners are on a much better level than in local prisons and a spirit of constructive planning for the future on release seems to be stimulated.

A second factor is the opportunity for re-building social ties. Broadly, the research indicates that prison visitation is associated with lower rates of recidivism and those receiving visits in custody have smoother transitions back to society (Bale & Mears, 2008; Cochran, 2014; Mitchell et al., 2016). Whilst the right to visitation is enshrined in section 35 of The Prison Rules (1999), and applicable to all prisoners in
England and Wales, the ‘quality’ of these visits varies as a function of security classification. This potentially mediates the protective effect of prison visitation (Turanovic & Tasca, 2022). For instance, in maximum security environments, visits are closely monitored by prison officers and in some cases, the visit might even be conducted in booths with glass partitions. Restrictions pertaining to frequency, duration, and physical touch are commonplace (Comfort, 2008; Dixey & Woodhall, 2012; Hutton, 2013; Wall, 2013). In contrast, visits in settings of lower security might take place in cafeteria style rooms with greater freedoms on movement and touch (Comfort, 2002) or indeed, might be permitted in the community away from the gaze of prison staff (Andvig et al., 2021). Turanovic and Tasca (2022) found that the effect of prison visitation on recidivism was attenuated in closed and maximum security prisons where the ability to listen and communicate, as Toch (2001, p. 380) frames it, is done by ‘muffled voices through impermeable partitions’. Visits in lower security prisons were said to enable greater connectedness in both a practical (e.g., housing, employment, parenting) and emotional (e.g., development of interpersonal relationships) sense (Turanovic & Tasca, 2022).

Thirdly, open prisons typically possess mechanisms that enable prisoners temporary release to the community. In England and Wales, the Release on Temporary Licence (RoTL) scheme permits prisoners access to the community for the purposes of finding or accessing education, training, or work; rebuilding family ties; familiarisation with their resettlement area; and other activities supporting reintegration into local communities (Ministry of Justice, 2019b). Research by the Ministry of Justice (2015) found that those who undergo a staged and individualised pathway to temporary release for employment or training reasons, were one-half as likely to re-offend versus those who did not (8% for Release on Temporary Licence
[RoTL]; 16% for the control group). Similar albeit less pronounced findings are reported in Baumer and colleagues (2009) in the Irish prison system. Those permitted leave of absence to spend time with family or engage in vocational activities were significantly less likely to be re-imprisoned at the end of the four-year follow-up, compared with those not permitted leave (43% vs. 48% for family leave and 42% vs. 46% for vocational leave). Furthermore, there may be a cumulative protective effect of RoTL against recidivism. That is, over a one-year follow-up, Hillier and Mews (2018) found a 0.5% reduction in the odds of re-offending for each additional day release in the community, whilst each additional overnight release was associated with a full 5% reduction in the odds of re-offending. Arguably, in comparison to closed prisons, open prisons have the infrastructure, expertise, and community links necessary to deliver temporary release schemes in the necessary volumes.

Taken together, there is evidence to indicate that open prisons provide an important and unique contribution to the resettlement of offenders in the community; a contribution which cannot easily be replicated by closed prisons.

1.3. The Risks Associated with Open Prisons

Whilst the above argues for the clear benefits of open prison placements, compared to closed prisons, in the staged release of offenders to the community, open prisons pose a novel risk to public safety. Given the absence of perimeter security, minimal supervision arrangements, limited restrictions on activity/movement, and open access to the public, there is an increased hazard that harmful behaviours may spill out into the community; behaviours which might be otherwise contained by the walls of a closed prison (cf. Price, 1971). The primary managed risk in open conditions is the risk of re-offending, particularly where there is
a real and tangible risk of harm to a victim. However, open prisons actively manage other forms of risk too, such as the risk of abscond and the risk of Temporary Release Failure (TRF). In England and Wales, absconding is defined as unlawfully gaining liberty for 15 minutes or more without overcoming a physical security restraint, while TRF is a failure to adhere to any condition included on the individual’s temporary release licence (Justice Data Lab, 2022). Indeed, absconds and TRFs create a heightened perception of risk to public safety (Doughty 2008; Tiplady-Bishop, 2022) albeit they only exceptionally result in violence or re-offending; a finding consistent across time and jurisdiction (Banks et al., 1975; Dissel, 2008; Hillier & Mews, 2018; Leitch, 1951; Porritt, 1982; see also Chapter 3 results).

Findings reported in Chapter 3 of this thesis demonstrate that absconds, re-offences and TRFs by open prison residents are rare events. Among a cohort of 316 prisoners released from two open prisons in England, the failure rates were 0.9% for re-offending, 1.3% for absconding, and 3.2% for TRFs. The relative infrequency of TRF events is elucidated in Hillier and Mews (2018). They analysed the frequency of release failures in a sample of prisoners released under the Release on Temporary Licence (RoTL) scheme from prisons in England and Wales in 2016 (on average, 47 incidences of RoTL per individual). Less than 0.1% of temporary releases resulted in release failure, i.e., breach of licence, failure to return to custody, or alleged offending; a failure rate of just 75 per 100,000 RoTLs (Hillier & Mews, 2018).

Yet release failures, no matter how few can have damaging repercussions for the legitimacy of an institution (cf. Dawar & Davis, 2014; HM Inspectorate of Prisons, 2014; Reichlin & Bloom, 1993). The impact has been documented most extensively by research in forensic secure hospitals but relevance to criminal justice samples can be inferred from inspectorate reports and newspaper articles. Reichlin and Bloom (1993)
describe the impact of abscond on the legitimacy of forensic hospitals as a function of the media scrutiny of the event and its marked public and political influence. Indeed, sustained political pressure to address the shortcomings can result in policy change (cf. HM Inspectorate of Prisons, 2014), change which, according to Moore (2000), can be disproportionate to the nature and outcome of the incident and, in some cases, adversely impact rehabilitation delivery. Recent legislative changes to the open prisons test in England and Wales, which allow the Secretary of State to veto transfers (Ministry of Justice, 2022c), is a potential case in point. A policy designed for the purpose of public protection is obstructing a whole cohort of indeterminate sentenced prisoners from open prisons (Hymas, 2022) and, as reviewed above, the mediating impact of these establishments on recidivism.

Even in the absence of policy change, such ‘failures’ have unintended negative effects at a micro-level. Staff members might feel angry, embarrassed, or guilty (McIndoe, 1986) and consequently adopt a risk averse, anti-rehabilitative approach to the management of other residents (Bowers et al., 2006). Yet, authoritarian approaches to risk management have been found to be disruptive to the social equilibrium of the environment, and contrary to intention, are associated with higher rates of aggression and absconding (Alexander, 2006; Urheim et al., 2011). This is incisively encapsulated by the autoethnographic account of a life-sentenced prisoner in Micklethwaite and Earle (2021, p. 538) who, reflecting on the ‘daily’ transfers of prisoners back to closed prisons as an authoritarian risk management approach, came to understand ‘the precariousness of my presence in the new environment’. Abscond becomes a viable option under such conditions. Additionally, the increased media attention which might follow an abscond is likely to exacerbate the perception of stigma amongst those that remain (Campagnolo et al., 2019; Reichlin & Bloom, 1993)
which has, itself, been associated with negative outcomes including higher rates of recidivism (Chiricos et al., 2007). Irrespective of victim harm then, it becomes imperative that open prisons have evidenced-based mechanisms for identifying, managing, and mitigating the risk of release failures.

1.4. The Challenges of Preventing Adverse Events such as Abscond or Re-offending

The prevention of adverse events such as abscond or re-offending is impeded by diverse factors. First, open prisons in England and Wales have limited influence over the re-categorisation of prisoners, i.e., stepping down from closed to open, thereby restricting the scope to proactively mitigate risk exposure. Typically, for determinate sentenced prisoners, the re-categorisation criterion is applied by prison managers at the closed prison where the individual is held. For indeterminate sentenced prisoners however, suitability is determined by the Public Protection Casework Section – on behalf of the Secretary of State – following a recommendation from the Parole Board (Ministry of Justice, 2020a). As per Leitch (1951), this design arguably prevents the selection of those who would, with some certainty, have been ‘successes’ on their return to the community. Nonetheless, such admission rules impede open prisons from preventing excessive risk exposure. As discussed earlier, open prisons, given their purpose, lack the physical infrastructure to detain those they house; have fewer procedural security measures to mitigate risk; and therefore, expose prisoners to risk as an inherent function of the re-categorisation process.

Second, there are methodological limitations to mitigating risk reactively through the monitoring and management of dynamic risk factors using established risk assessment protocols, like Structured Professional Judgment (SPJ) tools. Taking
recidivism first, there currently exists over two hundred risk/needs assessment tools for violence risk prediction (Singh et al., 2014a) founded in well-established theories of criminal conduct (e.g., Bonta & Andrews, 2017) and a substantial body of prediction studies and meta-analyses (Eisenberg et al., 2019; Gendreau et al., 1996; Goodley et al., 2022 [see Chapter 2]; Katsiyannis et al., 2018). Indeed, many contemporaneous risk tools yield moderate-to-large effect sizes (Singh et al., 2011; Tully et al., 2013; Yang et al., 2010). However, the accuracy of these tools is relative to the underlying base-rates of re-offending such that the number of false positives increases in samples with lower base rates of re-offending (Mossman, 2006). Given base-rates for recidivism are lower in open prison samples (Ministry of Justice, 2019a), compared to closed samples (Ministry of Justice, 2022b), there is an increased risk that open prisons might adopt risk-averse or authoritarian approaches with prisoners who pose a lower risk of recidivism. If we take, for example, a risk assessment tool with AUC=.80 accuracy to classify 100 offenders, in a sample in which 10% re-offend, 8/10 recidivists would be correctly classified as ‘high risk’ but with a high cost in false negatives: 18/80 non-recidivists would be misclassified. Eckhouse and colleagues (2019) note that this becomes particularly problematic amongst minority groups who might not be typically represented in majority-biased risk classification systems. Older offenders are one such group for whom risk is often overestimated (Monahan et al., 2017) such that the accurate assessment of those serving lengthy indeterminate sentences for serious offences has been considered a long-standing problem for criminal justice systems (Clark et al., 1993).

The true accuracy of established risk prediction protocols might also be diminished by the subjectivity inherent in any tool which relies on human participants to identify, collect, synthesise, and rate risk information (Beech et al., 2016). SPJ tools
are time-consuming to administer (Green et al., 2010) such that Ho and colleagues (2018) argue that time-constraints in under-resourced services can impact on the accurate discrimination of case-relevant factors resulting in flawed decision-making. Indeed, some studies have found poor levels of agreement when scoring items on SPJ tools or inadequate testing of inter-rater reliability (Baird, 2009; Duwe & Rocque, 2016).

Jones (2004) also argues that conventional risk assessment protocols are misapplied such that risk predictions are based in past, discrete episodes of behaviour rather than dynamic change over time. Similarly, Harris and Rice (2015) assert that dynamic risk factors become static in nature when measured only once.

Arguably, the accurate assessment of other forms of release failure in open prisons, such as abscond, is beset by greater challenges. The primary challenge is the paucity of literature identifying risk factors for absconding in open prison samples. Presently, based on custodial samples, there are just three quantitative studies (Emirali et al., 2020; McSweeney et al., 2011; Mews 2014) and a handful of unpublished qualitative studies (i.e., Berman-Roberts, 2015; Chant, 2015; Papworth, 2015; Picksley, 2016; Roberts, 2016) from which data on abscond or Temporary Release Failure (TRF) can be delineated. The evidence cautiously indicates that a history of absconding behaviour and a number of dynamic factors ‘pulling’ (e.g., family crises; conveying contraband) and ‘pushing’ (e.g., bullying, poor relationships with staff) prisoners away from open prison are relevant. However, all are limited by various methodological constraints. One of the critical limiting factors of this literature, described briefly earlier, is that admission to open prison is not randomised but selective. As such, the identification of risk factors for absconding will always be limited to the study of a small subset of the population exposed to the open prison
environment and selected, at least partially, on the basis that they present a low risk for abscond (c.f. Ministry of Justice, 2020a). Moreover, ‘technical violations’ limit the accurate identification of risk factors for abscond. Open prisons are permitted to return unsuitable candidates for rule infractions. Technical violations then, which temporally precede and therefore censor any potential failure event, result in the removal of crucial recidivistic information from the dataset (see Ostermann et al., 2020 for commentary). Absconds are rare events (see Chapter 3) and these factors also contribute to the low base rate problem hindering the accurate identification of risk factors for abscond.

In sum, procedural factors obstruct risk mitigation at the point of entry to open prison. As such, open prisons are required to have mechanisms to monitor and manage risk reactively. However, there are methodological impediments to reliably isolating factors predictive of failure in open prisons. Thus, open prisons must find other responsive means of identifying and mitigating risk manifestation.

1.5. The Role of Frontline Staff in Managing Risk in Open Prisons

In the absence of physical and procedural security controls to manage risk, relational or ‘dynamic security’ (Dunbar, 1985) becomes the principal method for managing risk. Relational security is defined as ‘the knowledge and understanding staff have of a patient and of the environment, and the translation of that information into appropriate responses and care’ (Department of Health, 2010, p. 5). As such, good relational security goes beyond simply building and maintaining good relationships with prisoners. It hinges upon knowing about that individual’s outside world (e.g., outward connections), their inside world (e.g., physical environment; personal world), the dynamics of that inside world (e.g., relationships with other
prisoners; prisoner mix) and crucially, the impact therein of changes within these domains. Indeed, if dynamic changes in these domains are responsible for ‘pulling’ and ‘pushing’ prisoners to abscond or re-offend (i.e., Berman-Roberts, 2015; Chant, 2015; Papworth, 2015; Picksley, 2016; Roberts, 2016), then arguably, information gleaned from knowing the prisoner and their environment has utility in ‘foiling’ any such plans at a very basic level.

Behavioural monitoring frameworks may be well suited as a potential means of risk identification in open prisons. Behavioural monitoring is based in two well established findings. First, that past behaviour (e.g., criminal history) is the best predictor of future behaviour (Bonta et al., 1998; Farrington et al., 1998; Mossman, 1994) and second, premised on the former, that behaviour – and in this case antisocial behaviour – is cross-situationally consistent (Farrington, 1978; Zamble & Porporino, 1990). Consequently, custodial behaviour should be observable in community behaviour and vice versa. Indeed, using behavioural analysis techniques, Clark and colleagues (1993) were able to identify offence-related behaviour similar to the index offence in 60% of prison behaviours, demonstrating experimentally that offence behaviour later manifested in prison behaviour. Taking the notion a step further, McDougall and colleagues (2013) demonstrated that it was possible to predict community recidivism on the basis of custodial behaviour, finding that frequency of concerning behaviours, irrespective of their functional link to the index offence, predicted recidivism. Moreover, risk prediction was highly accurate (92%). As such, behavioural monitoring has pedigree as an individualised and temporally responsive analysis of recidivism risk (Clark et al., 1993; Jones, 2004; McDougall et al., 2013; Pearson & McDougall, 2017) and may be utilised as an adjunct to good relational security practices.
Yet more progressively perhaps, the information gleaned from good relational or dynamic security practices might be used, not just to ‘foil’ risky behaviours, but to change factors – and/or change the individual’s interaction with those factors – pushing or pulling them away from open prison. To date, there has been a handful of small-scale studies reporting successful outcomes using risk assessment and behavioural analysis as the starting point for such interventions (cf. Tolisano et al., 2017; Ward & Bosek, 2002) but the current evidence remains limited.

Following a series of further offences by prisoners granted temporary release from open prisons in England and Wales in 2013, His Majesty’s Prison and Probation Service (HMPPS) adopted a behavioural monitoring policy framework (Enhanced Behaviour Monitoring [EBM]), with the purpose of providing assurances that ongoing risks (e.g., of harm; re-offending, or abscond) are appropriately identified and subsequently managed within open prisons, and during periods of temporary release (NOMS, 2015a). EBM consists of two elements. The first is a psychologist-led file review – a detailed and expert analysis of behaviours indicative of risk manifestation. The second is a behaviour monitoring framework for intervening with those deemed at heightened risk, to assist in their development of self-management strategies to mitigate emerging risks. The present author was temporarily redeployed to one of the sites of those serious further offences. I was tasked with reviewing the risks posed by the population of men convicted of sexual offences resident at the open prison, before taking up post permanently in May 2014, during which time I was responsible for implementing the EBM policy framework at the site. As such, I have direct experience of delivering the various aspects of EBM in an open prison – the opportunities and limitations therein – and more widely, the challenges of managing risk in an open prison.
As yet, there exists no systematic evaluation of the EBM framework as an effective means of managing risk in open prisons. Thus, the overarching aim of this thesis was to evaluate the impact of EBM on failure rates in open conditions and whether EBM is targeted at those posing the greatest risk for failure.

1.6. Outline of the Thesis

The overall aim of this thesis was to evaluate the impact of a behavioural monitoring framework – Enhanced Behaviour Monitoring (EBM) – implemented in open prisons in England and Wales in 2014, on reducing failure outcomes such as abscond, re-offending, and temporary release failure. To produce evidence of acceptable scientific rigour, it was unviable to conduct a simple comparison between a pre-selected experimental group (prisoners allocated to EBM following a Case File Review) and an unselected comparison group of prisoners from the remaining open prison population. The internal validity of such a comparison is threatened by selection bias and the uncontrolled differences between the two groups (Hollin, 2008; Wilson et al., 2005). As such, to inform this evaluation (Study 3), it was necessary to isolate a set of factors predictive of failure in open conditions upon which the two groups could be matched (Study 2). However, given the aforementioned dearth of literature into failure outcomes in offenders resident in open prisons, a preliminary examination of risk factors potentially related to such failure outcomes was critical. This was achieved via a review of the extant literature into absconds and temporary release failures and a survey of those with expertise in managing risk in open conditions, to augment a comprehensive meta-analysis of factors predictive of reincarceration in a sample of prisoners released from custody (Study 1). Each of these studies were written in a format to standalone for publication. As such, there is
unavoidable repetition amongst the chapters. An overview of the three studies and their respective designs is provided below.

1.6.1. **Study 1: Predictors of Recidivism Following Release from Custody: A Meta-Analysis**

Study 1 was a systematic review and meta-analysis of predictors for any form of recidivism (re-arrest, reconviction, re-imprisonment, or parole revocation) in the initial years (<3 years) following release from custody. The parameters of the meta-analysis were deliberately set, mirroring the timeline and risk exposure of those transferring to open prison. Open prisons hold adult males and represent first re-exposure to the community for those residents, thus only those studies examining adults (18 or over) released from custodial sentences were included. The three-year follow up period, indeterminate sentenced prisoners aside, corresponded to open prisons’ eligibility criteria of having less than three years left to serve (Ministry of Justice, 2020a); and thus represented the period in which prisoners are ‘at risk’ of failure. Finally, ‘failure’ in open conditions comes in various guises, a spectrum encompassing breach of licence through to re-offending. As such, the outcome measure utilised in the meta-analysis needed to be sufficiently broad for replication. To ensure identification of only those factors which most reliably predicted failure outcomes in the initial years following community re-exposure, the study also adopted several unique methodological approaches including a study quality assessment (Hayden et al., 2013). The final meta-analysis was based on 67 studies meeting the inclusion criteria and the study quality assessment.

The meta-analysis identified 17 factors which were associated with increased or decreased risk for recidivism in the immediate years preceding release from custody. These risk factors were consistent with the General Personality and
Cognitive Social Learning (GPCSL) theory; the predominant theory in the field explaining antisocial potential (Bonta & Andrews, 2017). These risk factors were predominantly static in nature, reflecting the dearth of high-quality studies examining dynamic risk factors for recidivism.

1.6.2. Study 2: Monitoring Prisoners Preparing for Release: Who ‘Fails’ in Open Conditions?

The primary aim of Study 2 was to isolate a set of factors predictive of increased risk for ‘failure’ in open prison conditions with a secondary aim of developing a set of guiding principles for the targeting of the Enhanced Behaviour Monitoring (EBM) framework. Given the damaging repercussions of failure events on the legitimacy of those organisations managing the risk (cf. Dawar & Davis, 2014; HM Inspectorate of Prisons, 2014; Reichlin & Bloom, 1993) it is imperative that open prisons have mechanisms for identifying, managing, and mitigating the risk of release failures. Twenty-six risk factors potentially relevant to the prediction of failure outcomes in open prisons were identified from the recidivism prediction meta-analysis in Study 1 and a review of the extant literature into failure outcome events more common to open prisons (e.g., absconds, temporary release failures (TRFs)). These predictor variables were pared down using a purposive model building strategy outlined in Hosmer and colleagues (2013).

Utilising a retrospective cohort design, 316 prisoners resident in open conditions were tracked until release or failure in open conditions. Most failures – 26.3% of all outcomes – were recalls to closed conditions for security reasons. Failures resulting from abscond, re-offending, or TRFs were otherwise ‘rare’ events. Community recidivism rates in the one-year following release were also low (4.7%)
thereby exposing an approach to risk across open prisons in England and Wales which is aversive, authoritarian, and disproportionate to the actual risk. The model for predicting security recall events was more accurate at identifying non-recalls (93.8%) than recalls (62.7%), an indicator that addressing the contextual factors for failure might hold greater potential than isolating individual-level factors discriminating recidivists.

1.6.3. **Study 3: Evaluation of an Enhanced Behavioural Monitoring System in UK Open Prisons**

The aim of Study 3 was to evaluate the impact on failure rates (i.e., abscond, re-offending, TRF), of the behavioural monitoring element of the Enhanced Behaviour Monitoring (EBM) framework. Given this behaviour monitoring phase is reserved for those deemed to be at ‘heightened risk’ for failure, the sample of men exposed to the intervention over the preceding six years was likely to be selective, and unrepresentative of the open prison population. As such, a simple comparison between the EBM group and an unselected comparison group of prisoners from the remaining open prison population was liable to bias. Yet, the correlation between failure outcomes and allocation to the behavioural monitoring phase of EBM was likely to be imperfect for two reasons. First, there is a paucity of literature into predictors of failure in open conditions upon which to target the EBM intervention. Second, allocation to the EBM intervention is decided by psychological professionals based on ‘current risk management related concerns’ (NOMS, 2015a, p.31) which is sufficiently subjective to assume variability in the application of the criteria. In the view of these potential complexities in the sample, ‘matching’ the experimental group
(i.e., EBM intervention) to a control group, based on those variables predictive of failure in Study 2, was a viable and robust evaluation strategy.

Using Propensity Score Matching (Rosenbaum & Rubin, 1983), all but three \((n = 171)\) of the 174 prisoners allocated to EBM in the overall sample \((N = 692)\) were matched to a control. An Intention To Treat (ITT) approach was adopted to evaluate the extent to which the EBM intervention was having the intended impact on failure rates regardless of completion of the intervention per protocol. However, given this approach has limitations in assessing the effect of the ‘full dosage’ of any given intervention (cf. Hollin, 2008; Kovach, 2020), the outcomes of those discharged from EBM management per-protocol were compared to a matched sub-group of control cases to evaluate the effect of ‘treatment received’ (TR) in full. Study 3 found that allocation to EBM was associated with higher rather than lower rates of recall to closed conditions although those completing EBM per-protocol (TR) were slightly more likely to survive in open conditions. The findings suggest that the rehabilitative impact of EBM is blunted and little more than a supervision tool for the purpose of detecting rule violations (Hyatt & Barnes, 2017; Petersilia & Turner, 1993). This is perhaps reflective of the socio-political context in which open prisons operate wherein staff, fearful of the consequences of serious failure outcomes such as absconding, are hypervigilant to the threat, at the expense of patient care (cf. Muir & Cochrane, 2012).
Chapter 2: Predictors of Recidivism Following Release from Custody: A Meta-Analysis

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Chapter 2: Predictors of Recidivism Following Release from Custody: A Meta-Analysis

Abstract

The reliable identification of those offenders at greatest risk of post-release recidivism is critically important given the 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 pro-criminal attitudes. Overall, static risk factors were superior to dynamic in predicting recidivism. These findings are explored 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.

Introduction

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 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, 2021); 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 (Ministry of Justice, 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 predict persistence in criminal behaviour. 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), pro-criminal 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 – history of antisocial behaviour, antisocial personality pattern, antisocial cognitions, and antisocial associates (‘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., 2019a, 2019b). Indeed, the conceptual distinction remains hypothetical. 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 (2019b) 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 recidivism risk prediction there is, as yet, no evidence that they are better risk predictors compared to static factors (Casey, 2016; Harris & Rice, 2015; Heffernan et al., 2019b).

**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 for 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 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. I 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, 2020b). Arguably therefore, and in the context of the increased workload demands within Probation Services (DeMichelle & Payne, 2018; Martin & Zettler, 2021), there is urgency in identifying those at higher risk of recidivism among samples pending custodial release. The study 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, the effect sizes for each factor were presented, 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 timeframe 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 from 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 pre-release prison environment or post-release community environment, 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, I 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, I 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. I also 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.

I coded all studies in the meta-analysis. The studies were rated independently by a postgraduate research assistant at the abstract screening phase. The ‘hard-to-code’ studies were rated independently by Dominic Pearson (supervisor) 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, I 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 the intention had been 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 in the appendices to this chapter, 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 \((0.74 - 1) \times 100\) 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 and colleagues (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%, I 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 reporting 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, consistent with other risk predictor meta-analyses (Hanson & Morton-Bourgon, 2004, 2005).

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 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). I 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.

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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.
Study Selection

Figure 2.1 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 ($\kappa = 0.62$). 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 ($Mdn = 0.75$). I conducted the risk of bias analysis with independent agreement from my supervisor on all but 15 studies ($\kappa = 0.75$). Disagreement was resolved through discussion. Based on Higgins (2013), all those studies presenting a high risk of bias ($n=61$) were removed as were eight further 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 dataset
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 in the appendices to this chapter.

Figure 2.1.

PRISMA Diagram for the Selection of Studies for the Present Meta-Analysis.
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 2.1. 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.

Table 2.1

Characteristics of Studies (n=43) Included in the Meta-Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Frequency (percent) (k = 43)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Publication source</td>
<td></td>
</tr>
<tr>
<td>Published</td>
<td>35 (81.4%)</td>
</tr>
<tr>
<td>Unpublished</td>
<td>8 (18.6%)</td>
</tr>
<tr>
<td>Country</td>
<td></td>
</tr>
<tr>
<td>United States</td>
<td>32 (74.4%)</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>5 (11.6%)</td>
</tr>
<tr>
<td>Canada</td>
<td>3 (7.0%)</td>
</tr>
<tr>
<td>Sweden</td>
<td>2 (4.7%)</td>
</tr>
<tr>
<td>New Zealand</td>
<td>1 (2.3%)</td>
</tr>
<tr>
<td>Gender</td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>17 (39.5%)</td>
</tr>
<tr>
<td>Female</td>
<td>4 (9.3%)</td>
</tr>
<tr>
<td>Both</td>
<td>22 (51.2%)</td>
</tr>
</tbody>
</table>
Year of publication

<table>
<thead>
<tr>
<th>Year of publication</th>
<th>Count (Percentage)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996-2003</td>
<td>9 (20.9%)</td>
</tr>
<tr>
<td>2004-2011</td>
<td>15 (34.9%)</td>
</tr>
<tr>
<td>2012-2017</td>
<td>19 (44.2%)</td>
</tr>
</tbody>
</table>

Sample sizes

<table>
<thead>
<tr>
<th>Sample sizes</th>
<th>Count (Percentage)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100-500</td>
<td>15 (34.9%)</td>
</tr>
<tr>
<td>501-1000</td>
<td>8 (18.6%)</td>
</tr>
<tr>
<td>1001-5000</td>
<td>11 (25.6%)</td>
</tr>
<tr>
<td>5001-10000</td>
<td>4 (9.3%)</td>
</tr>
<tr>
<td>10001-50000</td>
<td>4 (9.3%)</td>
</tr>
<tr>
<td>50001-100,000</td>
<td>1 (2.3%)</td>
</tr>
</tbody>
</table>

Follow up period (months)

<table>
<thead>
<tr>
<th>Follow up period (months)</th>
<th>Count (Percentage)</th>
</tr>
</thead>
<tbody>
<tr>
<td>6-12</td>
<td>12 (27.9%)</td>
</tr>
<tr>
<td>13-24</td>
<td>13 (30.2%)</td>
</tr>
<tr>
<td>25-36</td>
<td>14 (32.6%)</td>
</tr>
<tr>
<td>37-48</td>
<td>4 (9.3%)</td>
</tr>
</tbody>
</table>

Recidivism outcome variable

<table>
<thead>
<tr>
<th>Recidivism outcome variable</th>
<th>Count (Percentage)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rearrest</td>
<td>17 (39.5%)</td>
</tr>
<tr>
<td>Reconviction</td>
<td>15 (34.9%)</td>
</tr>
<tr>
<td>Reincarceration</td>
<td>6 (14.0%)</td>
</tr>
<tr>
<td>Parole revocation</td>
<td>2 (4.7%)</td>
</tr>
<tr>
<td>Any recidivism</td>
<td>3 (7.0%)</td>
</tr>
</tbody>
</table>

Note: k = number of samples included in the analysis

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 2.2 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).

Compared to prisoners of white race, 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 2.2 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 2.2. 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 the reference category of ‘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 2.2 which protected against recidivism was parole release (OR = 0.70, CI = 0.59, 0.82) but this was based on three studies only.
### Table 2.2

**Predictors of Recidivism – Multivariate Analyses**

<table>
<thead>
<tr>
<th>Predictor</th>
<th>$k$</th>
<th>$Ni$</th>
<th>OR$_w$</th>
<th>95% CI</th>
<th>OR$_w$</th>
<th>95% CI</th>
<th>$Q$</th>
<th>$I^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Possible risk factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of previous incarcerations$^a$</td>
<td>10</td>
<td>46820</td>
<td>1.60***</td>
<td>[1.36, 1.89]</td>
<td>1.37***</td>
<td>[1.30, 1.44]</td>
<td>61.21***</td>
<td>85.0</td>
</tr>
<tr>
<td>With outlier</td>
<td>11</td>
<td>101101</td>
<td>1.52***</td>
<td>[1.29, 1.80]</td>
<td>1.07***</td>
<td>[1.05, 1.09]</td>
<td>166.29***</td>
<td>94.0</td>
</tr>
<tr>
<td>Previous Parole Violation (yes=1, no=2)</td>
<td>9</td>
<td>70430</td>
<td>1.48***</td>
<td>[1.18, 1.91]</td>
<td>1.37***</td>
<td>[1.33, 1.41]</td>
<td>365.83***</td>
<td>98.0</td>
</tr>
<tr>
<td>Gender (male=1, female=0)</td>
<td>15</td>
<td>129880</td>
<td>1.47***</td>
<td>[1.31, 1.65]</td>
<td>1.41***</td>
<td>[1.32, 1.51]</td>
<td>27.64*</td>
<td>49.0</td>
</tr>
<tr>
<td>Index offence (property)$^b$</td>
<td>5</td>
<td>43968</td>
<td>1.36***</td>
<td>[1.24, 1.50]</td>
<td>1.35***</td>
<td>[1.27, 1.44]</td>
<td>6.32</td>
<td>37.0</td>
</tr>
<tr>
<td>With outlier</td>
<td>6</td>
<td>48665</td>
<td>1.31***</td>
<td>[1.16, 1.48]</td>
<td>1.32***</td>
<td>[1.24, 1.40]</td>
<td>13.19*</td>
<td>62.0</td>
</tr>
<tr>
<td>Race (black=1, white=0)</td>
<td>12</td>
<td>132664</td>
<td>1.33***</td>
<td>[1.19, 1.49]</td>
<td>1.44***</td>
<td>[1.37, 1.49]</td>
<td>42.52***</td>
<td>74.0</td>
</tr>
<tr>
<td>Drug abuse (present=1, absent=0)</td>
<td>14</td>
<td>38520</td>
<td>1.31***</td>
<td>[1.15, 1.50]</td>
<td>1.13***</td>
<td>[1.10, 1.17]</td>
<td>114.54***</td>
<td>89.0</td>
</tr>
<tr>
<td>Number of previous arrests$^a$</td>
<td>6</td>
<td>46442</td>
<td>1.18***</td>
<td>[1.09, 1.28]</td>
<td>1.09***</td>
<td>[1.08, 1.10]</td>
<td>18.21**</td>
<td>73.0</td>
</tr>
<tr>
<td>With outlier</td>
<td>7</td>
<td>51951</td>
<td>1.12***</td>
<td>[1.06, 1.18]</td>
<td>1.02***</td>
<td>[1.02, 1.02]</td>
<td>149.89***</td>
<td>96.0</td>
</tr>
<tr>
<td>History of mental illness (yes=1, no=0)</td>
<td>5</td>
<td>38753</td>
<td>1.12***</td>
<td>[1.05, 1.21]</td>
<td>1.12***</td>
<td>[1.05, 1.20]</td>
<td>3.04</td>
<td>0.00</td>
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<tr>
<td>Prior criminal record (yes=1, no=0)</td>
<td>15</td>
<td>12377</td>
<td>1.12***</td>
<td>[1.08, 1.16]</td>
<td>1.04***</td>
<td>[1.04, 1.05]</td>
<td>227.23***</td>
<td>94.0</td>
</tr>
<tr>
<td>Number of institutional infractions$^a$</td>
<td>4</td>
<td>24419</td>
<td>1.05$^+$</td>
<td>[1.00, 1.10]</td>
<td>1.02$^+$</td>
<td>[1.02, 1.02]</td>
<td>8.99*</td>
<td>67.0</td>
</tr>
<tr>
<td>With outlier</td>
<td>5</td>
<td>50953</td>
<td>1.02***</td>
<td>[1.01, 1.03]</td>
<td>1.02***</td>
<td>[1.02, 1.02]</td>
<td>152.97***</td>
<td>97.0</td>
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<tr>
<td>Age at release</td>
<td>27</td>
<td>157792</td>
<td>0.96***</td>
<td>[0.95, 0.97]</td>
<td>0.97***</td>
<td>[0.97, 0.97]</td>
<td>1572.66***</td>
<td>98.0</td>
</tr>
<tr>
<td>Index offence: Drugs</td>
<td>9</td>
<td>85056</td>
<td>0.86***</td>
<td>[0.75, 0.98]</td>
<td>0.83***</td>
<td>[0.79, 0.88]</td>
<td>28.47***</td>
<td>72.0</td>
</tr>
<tr>
<td>Employed prior to custody (yes=1, no=0)</td>
<td>4</td>
<td>14708</td>
<td>0.84***</td>
<td>[0.78, 0.91]</td>
<td>0.84***</td>
<td>[0.78, 0.91]</td>
<td>1.53</td>
<td>0.00</td>
</tr>
<tr>
<td>Index offence: Violence$^a$</td>
<td>4</td>
<td>49332</td>
<td>0.74***</td>
<td>[0.67, 0.83]</td>
<td>0.74***</td>
<td>[0.67, 0.83]</td>
<td>1.25</td>
<td>0.00</td>
</tr>
<tr>
<td>With outlier</td>
<td>5</td>
<td>51595</td>
<td>0.83$^+$</td>
<td>[0.65, 1.01]</td>
<td>0.83$^+$</td>
<td>[0.75, 0.91]</td>
<td>14.98**</td>
<td>73.0</td>
</tr>
</tbody>
</table>
### Potentially misleading risk factors

<table>
<thead>
<tr>
<th>Variable</th>
<th>k</th>
<th>N</th>
<th>ORw</th>
<th>[95% CI]</th>
<th>ORw</th>
<th>[95% CI]</th>
<th>Q</th>
<th>I²</th>
</tr>
</thead>
<tbody>
<tr>
<td>History of alcohol abuse (yes=1; no=0)</td>
<td>4</td>
<td>17303</td>
<td>1.10</td>
<td>[0.98, 1.23]</td>
<td>1.05†</td>
<td>[1.00, 1.09]</td>
<td>5.62</td>
<td>47.0</td>
</tr>
<tr>
<td>With outlier</td>
<td>5</td>
<td>17873</td>
<td>1.25†</td>
<td>[1.03, 1.50]</td>
<td>1.06***</td>
<td>[1.02, 1.11]</td>
<td>19.47***</td>
<td>79.0</td>
</tr>
<tr>
<td>Time served</td>
<td>10</td>
<td>81520</td>
<td>1.00</td>
<td>[0.99, 1.00]</td>
<td>1.00***</td>
<td>[0.99, 1.00]</td>
<td>68.78***</td>
<td>87.0</td>
</tr>
<tr>
<td>Education level (high school qualification=1; none=0)</td>
<td>6</td>
<td>73493</td>
<td>0.93</td>
<td>[0.82, 1.06]</td>
<td>0.95***</td>
<td>[0.95, 0.95]</td>
<td>9.02</td>
<td>45.0</td>
</tr>
<tr>
<td>With outliers</td>
<td>8</td>
<td>86957</td>
<td>0.88</td>
<td>[0.60, 1.29]</td>
<td>0.95***</td>
<td>[0.95, 0.95]</td>
<td>466.42***</td>
<td>98.0</td>
</tr>
<tr>
<td>Ethnicity: Hispanic (Hispanic=1; White =0)</td>
<td>5</td>
<td>66036</td>
<td>0.93</td>
<td>[0.78, 1.11]</td>
<td>0.86***</td>
<td>[0.80, 0.92]</td>
<td>8.89</td>
<td>55.0</td>
</tr>
<tr>
<td>With outlier</td>
<td>6</td>
<td>92570</td>
<td>0.86</td>
<td>[0.66, 1.12]</td>
<td>0.76***</td>
<td>[0.72, 0.81]</td>
<td>54.82***</td>
<td>91.0</td>
</tr>
<tr>
<td>Intensive community supervision (yes=1; no=0)</td>
<td>5</td>
<td>101748</td>
<td>0.85</td>
<td>[0.55, 1.30]</td>
<td>0.63***</td>
<td>[0.60, 0.67]</td>
<td>76.16***</td>
<td>95.0</td>
</tr>
<tr>
<td>Employed at follow up (yes=1; no=0)</td>
<td>7</td>
<td>5815</td>
<td>0.75</td>
<td>[0.53, 1.06]</td>
<td>0.72***</td>
<td>[0.66, 0.80]</td>
<td>56.45***</td>
<td>89.0</td>
</tr>
<tr>
<td>With outlier</td>
<td>8</td>
<td>7030</td>
<td>0.64*</td>
<td>[0.42, 0.97]</td>
<td>0.64***</td>
<td>[0.59, 0.71]</td>
<td>114.23***</td>
<td>94.0</td>
</tr>
</tbody>
</table>

Note. k = number of studies included in the analysis; N = number of prisoners included in the sample; ORw = mean weighted odds ratio; CI = confidence interval of ORw ; Q = test of homogeneity of effect sizes; I² = 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.

- One outlier removed
- Two outliers removed
- †p<0.1, *p < 0.05, **p < 0.01, ***p < 0.001

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.
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 2.3. Sufficient data were available to draw conclusions about 17 factors. Ten of these predicted recidivism and are presented in Table 2.3 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 = 2.47 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 2.3. 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.

Table 2.3

Predictors of Recidivism – Bivariate Analyses

<table>
<thead>
<tr>
<th>Predictor</th>
<th>k</th>
<th>N</th>
<th>ORw</th>
<th>95% CI</th>
<th>ORw</th>
<th>95% CI</th>
<th>Q</th>
<th>( I^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Possible risk factors</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of previous incarcerations(^a)</td>
<td>5</td>
<td>4768</td>
<td>2.13***</td>
<td>[1.61, 2.81]</td>
<td>2.15***</td>
<td>[1.93, 2.41]</td>
<td>22.40***</td>
<td>82.0</td>
</tr>
<tr>
<td>With outliers</td>
<td>6</td>
<td>8035</td>
<td>2.47***</td>
<td>[1.63, 3.75]</td>
<td>2.81***</td>
<td>[2.56, 3.08]</td>
<td>93.13***</td>
<td>95.0</td>
</tr>
<tr>
<td>Drug abuse (present=1, absent=0)</td>
<td>13</td>
<td>13588</td>
<td>1.75***</td>
<td>[1.30, 2.38]</td>
<td>1.93***</td>
<td>[1.80, 2.07]</td>
<td>187.37***</td>
<td>94.0</td>
</tr>
<tr>
<td>Index offence: Property</td>
<td>5</td>
<td>10430</td>
<td>1.58***</td>
<td>[1.32, 1.90]</td>
<td>1.64***</td>
<td>[1.48, 1.81]</td>
<td>8.97†</td>
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<tr>
<td>Number of previous convictions</td>
<td>6</td>
<td>7207</td>
<td>1.54***</td>
<td>[1.08, 2.18]</td>
<td>1.36***</td>
<td>[1.27, 1.45]</td>
<td>48.66***</td>
<td>90.0</td>
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<tr>
<td>Criminal attitudes(^a)</td>
<td>5</td>
<td>3083</td>
<td>1.52***</td>
<td>[1.33, 1.73]</td>
<td>1.52***</td>
<td>[1.33, 1.73]</td>
<td>2.54</td>
<td>0.0</td>
</tr>
<tr>
<td>With outlier</td>
<td>6</td>
<td>3242</td>
<td>1.67***</td>
<td>[1.33, 2.08]</td>
<td>1.59***</td>
<td>[1.40, 1.80]</td>
<td>12.22**</td>
<td>59.0</td>
</tr>
<tr>
<td>Number of institutional infractions</td>
<td>4</td>
<td>1987</td>
<td>1.45***</td>
<td>[1.17, 1.80]</td>
<td>1.45***</td>
<td>[1.17, 1.80]</td>
<td>1.95</td>
<td>0.0</td>
</tr>
<tr>
<td>Previous assault/violence(^a) (yes=1; no=0)</td>
<td>4</td>
<td>7183</td>
<td>1.45***</td>
<td>[1.33, 1.58]</td>
<td>1.45***</td>
<td>[1.33, 1.58]</td>
<td>2.73</td>
<td>0.0</td>
</tr>
<tr>
<td>With outlier</td>
<td>5</td>
<td>7482</td>
<td>1.35*** [1.16, 1.57]</td>
<td>1.42*** [1.31, 1.54]</td>
<td>10.63*** 62.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race (Black=1, White=0)</td>
<td>12</td>
<td>15428</td>
<td>1.40*** [1.25, 1.56]</td>
<td>1.49*** [1.39, 1.59]</td>
<td>18.08† 39.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Gender (male=1, female=2)</td>
<td>12</td>
<td>75547</td>
<td>1.39*** [1.21, 1.58]</td>
<td>1.25*** [1.21, 1.29]</td>
<td>93.84*** 88.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment problems (yes=1, no=0)</td>
<td>4</td>
<td>2476</td>
<td>1.26*** [1.09, 1.45]</td>
<td>1.26*** [1.09, 1.45]</td>
<td>0.75 0.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Offence type: Violence</td>
<td>6</td>
<td>5132</td>
<td>0.92** [0.86, 0.97]</td>
<td>0.92** [0.86, 0.97]</td>
<td>4.01 0.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With outliers</td>
<td>9</td>
<td>12948</td>
<td>0.71 [0.45, 1.13]</td>
<td>0.76*** [0.72, 0.80]</td>
<td>402.96*** 98.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Marital status (married=1, single=0)</td>
<td>9</td>
<td>8361</td>
<td>0.70*** [0.62, 0.80]</td>
<td>0.73*** [0.67, 0.79]</td>
<td>13.47 41.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With outlier</td>
<td>10</td>
<td>9991</td>
<td>0.73*** [0.61, 0.86]</td>
<td>0.88*** [0.83, 0.92]</td>
<td>45.74 80.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age at release</td>
<td>19</td>
<td>23411</td>
<td>0.62*** [0.53, 0.73]</td>
<td>0.99*** [0.99, 0.99]</td>
<td>52.37 93.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Completion of a structured programme to address risk factors (yes=1; no=0)</td>
<td>4</td>
<td>11972</td>
<td>0.60*** [0.45, 0.80]</td>
<td>0.68*** [0.62, 0.73]</td>
<td>16.49 82.0</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>With outlier</td>
<td>5</td>
<td>12707</td>
<td>0.73 [0.51, 1.06]</td>
<td>0.70 [0.65, 0.75]</td>
<td>40.45*** 0.90</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Potentially misleading risk factors

| Education level (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; Nᵢ = number of prisoners included in the sample; ORw = mean weighted odds ratio; CI = confidence interval of ORw; Q = test of homogeneity of effect sizes; I² = 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

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-
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 has on the accuracy of risk assessments. I 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). The interplay between moderator variables and individual risk predictors is complex, and in my view, 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 was of insufficient quality to be included in this meta-analysis with prognostic factor measurement undermining the quality assessment of several of those papers. Thus 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., 2019b). 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., 2019b).

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. I 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 of these 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 is 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., 2019b). 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.
In the published article, the table below was included as supplementary material.

**Table 2.4**

*Predictors of Time to Recidivism – Multivariate Analyses*

<table>
<thead>
<tr>
<th>Predictor</th>
<th>Random effects</th>
<th>Fixed effects</th>
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<tbody>
<tr>
<td></td>
<td><strong>k</strong></td>
<td><strong>N_i</strong></td>
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<tr>
<td><strong>Possible risk factors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of previous incarcerations^b</td>
<td>4</td>
<td>17196</td>
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<td>Gender (male=1, female=0)</td>
<td>9</td>
<td>66779</td>
</tr>
<tr>
<td>Index offence: Property</td>
<td>8</td>
<td>35283</td>
</tr>
<tr>
<td>Drug abuse (present=1, absent=0)</td>
<td>5</td>
<td>5722</td>
</tr>
<tr>
<td>Prior criminal record (yes=1; no=0)</td>
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<td>37011</td>
</tr>
<tr>
<td>Age at release</td>
<td>19</td>
<td>79163</td>
</tr>
<tr>
<td>Employed prior to custody (yes=1; no=0)</td>
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<td>2727</td>
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<td>Parole Release^a (yes=1; no=0)</td>
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<td>5617</td>
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<td>With outlier</td>
<td>5</td>
<td>7534</td>
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<tr>
<td><strong>Potentially misleading risk factors</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Race (black=1, white=0)</td>
<td>8</td>
<td>22461</td>
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<tr>
<td>Index offence: Drugs</td>
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<td>70738</td>
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<tr>
<td>Race: Hispanic (hispanic=1; white 0)</td>
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<td>5937</td>
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<tr>
<td>Education level (high school qualification=1; none=0)</td>
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<td>2298</td>
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<td>Time served</td>
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<tr>
<td>Index offence: Violence</td>
<td>7</td>
<td>56608</td>
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</tbody>
</table>

Note. k = number of studies included in the analysis; N_i = number of prisoners included in the sample; 
HR_w = mean weighted hazard ratio; CI = confidence interval of HR_w ; 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)
*p < 0.05, **p < 0.01, ***p < 0.001
Chapter 3: Monitoring prisoners preparing for release: Who ‘fails’ in open prison conditions?

A manuscript based on this chapter was submitted for publication and is currently under review.

Chapter 3: Monitoring prisoners preparing for release: Who ‘fails’ in open prison conditions

Abstract
Open prisons play a vital role in offender rehabilitation and resettlement but absconds, temporary release failures (TRFs), and re-offences have damaging implications for the legitimacy of these institutions. Identifying and mitigating the risk for such ‘failures’ is crucial. The present study examined predictors of failure in a sample of 316 adult male prisoners in two open prisons in England and Wales. Almost one-third \((n=100)\) of the sample failed in open conditions, the greatest proportion \((n=83, \text{26.3\%})\) instigated by the prison to maintain security and good order (security recall). Yet, only seven re-offended in the year following custodial release. Absconds, custodial re-offences, and TRFs were rare events. Regression analysis identified five factors predicting security recall. Current behaviour, rather than static/historical risk factors, more reliably predicted such failures. Behavioural monitoring and systemic policy re-evaluation are proposed as way of mitigating failures in open prisons.

Keywords
Abscond; behaviour monitoring; open prisons; recidivism; risk management; temporary release failure

Introduction
Minimum security or ‘open’ prisons, and in particular, the temporary absence/release schemes utilised in such regimes, play an important and unique role in the rehabilitation, preparedness, and resettlement of ‘high’ risk and long-term prisoners, as they transition back to the community. Gradual re-exposure to the community
may convey benefits for prisoners and the wider community, foremostly moderating
the risk of recidivism (Cheliotis, 2008; Hillier and Mews, 2018; Ministry of Justice,
2015, 2019). Temporary release activities supporting successful resettlement include
finding stable accommodation, securing work or training, building family ties, and
reintegration into local communities (Ministry of Justice, 2013a, 2013b). Indeed,
temporary release - the process by which prisoners are permitted leave from prison
for the purpose of engaging in activities to support their resettlement - provides
opportunities to test prisoners in conditions akin to those faced on leaving prison.
Temporary release failures are typically rare. Hillier and Mews (2018) report that
there were 7,000 individuals released under the Release on Temporary Licence (RoTL)
scheme from prisons in England and Wales in 2016 (on average, 47 incidences of RoTL
per individual) with less than 0.1% resulting in release failure, i.e., breach of licence,
failure to return to custody, or alleged offending; a failure rate of just 75 per 100,000
RoTLs. Yet release failures, irrespective of victim harm, can have damaging
repercussions for the legitimacy of an institution (cf. Dawar and Davis, 2014; HM
Inspectorate of Prisons, 2014). While escalating risk can be mitigated in custodial
settings by transferring the prisoner back to secure conditions (i.e., security recall),
this is costly and potentially iatrogenic. Cautionary tales resound from Alexander
(2006) and Beijersbergen and colleagues (2016) who attribute adverse outcomes such
as abscond and re-offending to procedurally unjust rule enforcement. To maintain a
rehabilitative environment that prepares for community reintegration, identifying
those individuals genuinely at heightened risk for failure is a necessary first step.
Reviewed below are those factors known to be linked with adverse outcomes such as
abscond and re-offending.
Predicting Risk of Failure

There is a substantial body of evidence underpinning the prediction of recidivism by offenders released into the community (see Chapter 2 and prior meta-analyses by Eisenberg et al., 2019; Gendreau et al., 1996; Katsiyannis et al., 2018) which serves as a potential starting point for predicting failure amongst those residing in open prisons, given consistency observed between custodial and community re-offence behaviours (McDougall et al., 2013). These meta-analyses broadly support Bonta and Andrews’ (2017) General Personality and Cognitive Social Learning (GPCSL) theory of a ‘central eight’ risk factors for recidivism. These risk factors are as follows: a History of CriminalBehaviour (early, persistent and varied criminal activity), Antisocial Personality Pattern (impulsive, callous and aggressive disposition), Pro-criminal Attitudes (attitudes condoning antisocial behaviour), Antisocial Companions, Family/Marital (lack of prosocial support and conflictual intimate relationships), School/Work (poor engagement, performance and relationships within), Leisure (low engagement and satisfaction in prosocial leisure pursuits), and Substance Abuse. The meta-analysis in Chapter Two (Goodley et al., 2022) focused on adults sentenced to and released from custody. This review identified 17, largely static/historical, predictors of recidivism, the majority of which could be accounted for within the four domains of antisocial potential (‘big four’: Andrews et al., 2006) such as number of previous contacts with the criminal justice system, holding pro-criminal attitudes, and institutional misconduct. These risk factors showed a consistent albeit small relationship with recidivism across jurisdictions and heterogeneous samples.

Substantially less attention has been given to identifying risk factors for absconding and failure on temporary release. Absconding from forensic hospital facilities has received most attention. The following are consistently reported as
predictors of abscond in low secure psychiatric units: a history of abscond attempts; substance misuse; higher risk ratings on the Historical Clinical Risk-20 (HCR-20); and evidence of non-compliance (Cullen et al., 2015; Martin et al., 2018; Wilkie et al., 2014). Absconders in these samples were variously motivated. The predominant motivation was instrumental in nature (goal-directed) and often resulted following substance misuse and/or an adverse event (e.g., conflict on the unit; family crises). Boredom and frustration were also widely represented, as were absconds following periods of mental illness. Absconding impulsively/opportunistically or incidentally, e.g., losing track of time on release, was uncommon in these samples (Martin et al., 2018; Mezey et al., 2015; Simpson et al., 2015; Wilkie et al., 2014). In a prospective study of absconsion incidents, Cullen and colleagues (2015) found that in-hospital behaviour, namely verbal aggression and substance misuse, discriminated those who absconded from those who did not, with greatest reliability.

Presently there are just three published studies with custodial samples from which data on abscond or Temporary Release Failure (TRF) can be delineated (Emirali et al. 2020; McSweeney et al., 2011; Mews, 2014). McSweeney and colleagues (2011) explored predictors for abscond in a sample of 2,312 (2.4%) of a possible 99,835 prisoners. The sample was identified as an abscond or escape risk, conflating two distinct behaviours. Likewise, it is unclear why those identified as a potential risk were included in the sample given there were 362 abscond events during the study period. Nonetheless, they identified the following correlates predictive of increased risk: having served two or more custodial sentences; having outstanding needs in each of the ten criminogenic areas assessed in the Offender Assessment System (OASys); serving a sentence for robbery; and, having an offending career longer than average (i.e., spanning seven years). Other potential predictors were factors typically
associated with re-offending such as being male, having served previous custodial sentences, and, presenting with a high likelihood of reconviction (measured using the OASys assessment). Emirali and colleagues (2020) compared a group of absconders against a control group and identified one predictor of abscond: number of previous offences. However, this study was based on a small sample of prisoners (N=61).

Mews (2014) analysed predictors of absconding in a sample of 23,701 prisoners, 347 (1.5%) of which were recorded as having an absconding incident. This larger study identified two predictors for absconding: a previous absconding incident, and previous TRF. Only the latter remained statistically significant after controlling for several other historical and demographic variables. However, the study was limited to exploring the predictive ability of a small number of static variables, which, given Cullen et al.’s (2015) analysis showing the relative value of in-hospital behaviour, are perhaps sub-optimal for discriminating absconding events.

A handful of unpublished qualitative studies conducted in English prisons, have also been conducted into the motivations underpinning the decision to abscond, revealing potentially promising dynamic risk variables (Berman-Roberts, 2015; Chant, 2015; Flowers, 2014; Papworth, 2015; Picksley, 2016; Roberts, 2016). These studies identified several ‘push’ (avoidance-focused) and ‘pull’ (approach-focused) factors. Push factors included prisoners feeling unsafe (e.g., threats, intimidation), often linked to drug debts; facing barriers to progression (e.g., denial of temporary release); struggling to adapt to the less structured regime of open prison; avoiding further punishment for misdemeanours (e.g., failing a drugs test); and experiencing poor relationships with staff. Pull factors included absconding to convey contraband (e.g., substances) into the prison; and responding to family pressures. These findings, however, remain speculative.
The Current Study

Following a series of serious further offences by prisoners granted temporary release from open prisons in England and Wales in 2013, the then Justice Secretary commissioned an internal review into the use of the RoTL scheme. The review concluded that a uniform approach had developed to managing all prisoners, with access to RoTL having become an expectation and not, crucially, a privilege predicated on comprehensive risk evaluation (HM Inspectorate of Prisons, 2014). This led to new guidelines being issued (NOMS, 2015b) alongside an Enhanced Behaviour Monitoring (EBM) system (NOMS, 2015a) designed to ensure that ongoing risks (i.e., abscond, harm, re-offending) posed by offenders in open conditions are appropriately identified and managed.

EBM consists of two elements: i) a psychologist-led case file review – detailing the risks posed by the prisoner in open conditions and, ii) a behavioural monitoring intervention – a wraparound package of support consisting of collaborative goal setting, behavioural feedback, and coaching of positive alternative behaviours – reserved for those deemed at heightened risk for ‘failing’. However, there is little guidance beyond ‘current risk management concerns’ regarding which prisoners should be targeted for the additional monitoring and support of EBM.

Thus, the primary aim of the present study was to isolate a set of factors predictive of increased risk of failure in open conditions. Given the limited research this is crucial; open prison placement and temporary release schemes prior to release are expected to impact positively on recidivism rates (Cheliotis, 2008; Hillier & Mews, 2018; Ministry of Justice, 2015, 2019) but their existence is frequently threatened by release failures (cf. Dawar & Davis, 2014). The secondary aim of this study was to identify the extent to which failure in open conditions equates to later community re-
offending and so consider whether EBM should be targeted at those who infringe custodial rules. Ultimately, by modelling those at ‘heightened’ risk of failure, the aim was not only to ensure allocation to the EBM scheme in England and Wales is data-driven, but more widely, to develop a set of guiding principles to help policymakers internationally to utilise open prison placements safely, given their resettlement benefits.

Method

Study Sample and Design

The current study adopted a retrospective cohort design. Prisoners selected were resident in two open prisons within England and Wales holding male prisoners aged 18 and above, and subject to psychologist-led Case File Reviews (CFRs) as part of the Enhanced Behaviour Monitoring (EBM) scheme. Eligible or ‘Restricted RoTL’ prisoners were those who met one or more of the following criteria as per Prison Service Instruction 13/2015 (NOMS, 2015b): serving an indeterminate sentence; subject to Multi Agency Public Protection Arrangements (MAPPA); and/or, assessed as high or very high risk of harm on the Offender Assessment System (OASys) risk assessment tool (Home Office, 2006). The whole sample had progressed through higher security classifications of prison to open conditions.

Prisoners on whom CFRs had been completed between 2 June and 22 July 2014 were selected for the study. The time period reflects the initial phase of EBM implementation in open prisons across England and Wales – the psychologist-led CFR. This time period was selected to avoid any confounding effect that the second phase of EBM – a behavioural monitoring intervention – might have on failure rates and thus on identifying predictors of failure. Basic demographic details pertaining to those
eligible for the study were recorded on electronic spreadsheets from which it was possible to trace their custodial records.

Table 3.1

Sample Characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Measure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, $M_{years}$ (SD, Range)$^1$</td>
<td>40.1 (13.1, 20-81)</td>
</tr>
<tr>
<td>Previous convictions, $M_{number}$ (SD, Range)$^2$</td>
<td>7.2 (7.9, 0-40)</td>
</tr>
<tr>
<td>Previous incarcerations, $M_{number}$ (SD, Range)$^3$</td>
<td>2.3 (3.6, 0-21)</td>
</tr>
<tr>
<td>Time at risk (open conditions) $M_{days}$ (SD, Range)$^4$</td>
<td>548.3 (350.4, 55-2180)</td>
</tr>
<tr>
<td>Index offence (%)</td>
<td></td>
</tr>
<tr>
<td>Burglary</td>
<td>5.1</td>
</tr>
<tr>
<td>Drug</td>
<td>2.5</td>
</tr>
<tr>
<td>Fraud</td>
<td>1.6</td>
</tr>
<tr>
<td>Robbery</td>
<td>14.2</td>
</tr>
<tr>
<td>Sexual</td>
<td>31.0</td>
</tr>
<tr>
<td>Violence</td>
<td>38.6</td>
</tr>
<tr>
<td>Other</td>
<td>7.0</td>
</tr>
<tr>
<td>Sentence type (%)</td>
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</tr>
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</tr>
<tr>
<td>Indeterminate for Public Protection</td>
<td>32.0</td>
</tr>
<tr>
<td>Life</td>
<td>28.8</td>
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<tr>
<td>Substance misuse (%)</td>
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</tr>
<tr>
<td>Yes</td>
<td>54.4</td>
</tr>
<tr>
<td>No</td>
<td>45.6</td>
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<tr>
<td>Mental illness (%)</td>
<td></td>
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<tr>
<td>Yes</td>
<td>26.6</td>
</tr>
<tr>
<td>No</td>
<td>73.4</td>
</tr>
</tbody>
</table>

$^1$ Mdn = 39  
$^2$ Mdn = 4  
$^3$ Mdn = 1  
$^4$ Mdn = 511

The eligible population comprised of 322 prisoners. Six were removed from the sample: three because it was not possible to trace their records,$^1$ and three due to
their being removed for procedural reasons (i.e., they no longer met the eligibility criteria). In total, the final sample included 316 participants. Table 3.1 shows the sample characteristics.

**Data and Measures**

**Predictors**

Risk predictors were identified from the research literature into absconding, release failure, and re-offending (reviewed above). The list was augmented by consulting with a group of applied psychologists with expertise in working in open conditions and implementing EBM. Data pertaining to these predictors were accessed from a variety of data sources including: the EBM CFR record, and national operational databases for the management of offenders such as the National Offender Management Information System (NOMIS), Offender Assessment System (OASys), and the Public Protection Unit Database. Twenty-six risk factors potentially relevant to the above outcomes were identified. This included socio-demographic factors such as age at CFR, and previous employment prior to custody, and, criminal history variables including number of previous convictions, number of previous incarcerations, index offence type, range of previous convictions, sentence type, and whether the offending career spanned a period of seven years or more, as identified by McSweeney and colleagues (2011). Prior parole revocation, prior absconding, and prior temporary release failure were also recorded. Medical history variables included history of mental illness, personality disorder, and substance misuse disorders. Behavioural risk factors included the number of behavioural incentives and warnings received in the one-year prior to transferring to open conditions. These were also recorded in the six months prior to release or the failure event alongside any reported adverse events and adjudications. The total number of adjudications across the prison sentence was
also recorded. Risk assessment variables included the Offender Group Reconviction Scale (OGRS3) (Howard et al., 2009), OASys Violence Predictor (OVP) (Howard & Dixon, 2012) score and a summary ‘highest’ risk score; the highest risk category attributed to that individual on any static risk assessment tool.²

**Outcome Measure**

There were four types of outcome measure: abscond, custodial re-offence, temporary release failure (TRF), and security recall. Collectively they are referred to as ‘failure’ here. Abscond was defined as unlawfully gaining liberty for 15 minutes or more without overcoming a physical security restraint. TRF was defined as a failure to adhere to any condition included on the individual’s temporary release licence. Custodial re-offence was defined as reconviction for any alleged offence, occurring either within or outside of the prison boundaries, whilst resident in open conditions. Security recalls were recalls to secure conditions, initiated by a Governor, typically following a breach of the prison rules, deemed indicative of an intolerable increase in the individual’s risk. Participants were tracked until release or failure in open conditions – whichever occurred first. This was used to classify the outcome event (success/failure in open conditions) from which it might be possible to predict who fails in open conditions. This follow-up period represented time period 1.

Time period 2 commenced from the date of release from custody. Participants were tracked for one year or until a community re-offence – whichever occurred first. The purpose of the community follow-up was to identify those who re-offended in the one-year following release from open conditions, to understand the community re-offending outcomes of those who failed and those who succeeded in open conditions. Six of the individuals successful in graduating from open prison (time period 1) re-offended in the community (time period 2). Given their offending shortly following
release, it seemed contraindicative to categorise these individuals as ‘successful’ open prison graduates; arguably they had masked behaviours indicative of ongoing risk which quickly manifested in the community, and which might otherwise have been addressed in custody, had the concerns been identified. Nonetheless, they were technically successful in navigating open conditions so they were removed from the data analysis investigating predictors of failure.

These data were primarily located using NOMIS. The data were cross-referenced against other records to validate the failure or custodial re-offence. In a small number of cases the custodial failure could not be validated; the decision to fail was clearly overturned within a 28-day period and the individual returned to open conditions. Such cases were not classified as a failure and the follow-up period continued until the release or valid failure.

Data pertaining to custodial failure and community recidivism were collated in December 2020. All participants had graduated or ‘failed’ in open conditions at the end of the follow-up period and were included in the analyses. The average time spent in open conditions was 548 days.

**Analytical Strategy**

The data analysis was split into two parts. Part one focused on the Security recall group; the largest ‘failure’ group \( n=83, 26.3\% \), see Results). The other failure groups (abscond, TRF, custodial re-offence) amounted only to an additional five percent of the sample. Given the substantive differences between the failure types, pooling the groups into a general failure outcome variable was inappropriate. There was merit in identifying the security recall group in open conditions for future intervention, given the long-term community outcomes for those recalled to secure conditions in this sample did not result in community re-offending \( n = 7, 8.4\% \), see
Logistic regression analyses were employed to examine which variables predicted security recall. Harrell and colleagues (1996) suggest that to have predictive discrimination that validates on a new sample, no more than $m/10$ predictor variables should be examined in the multiple regression model where $m$ is the number of participants in the less frequent outcome category, in this case, security recall ($n=83$). As such, it was necessary to reduce from 26, to a maximum of eight, the number of predictor variables included in the final model. This was achieved by following the purposeful model building strategy in Hosmer et al. (2013), the stages of which are outlined in Table 3.2. An additional step of removing variables with collinearity of $|r| > 0.8$ was also included; retaining for bivariate analyses only, the collinear variable which showed the strongest relationship with security recall. Field (2005) advocates $r > 0.8$ as an appropriate indicator for when collinearity distorts model estimation and prediction.

Six independent variables were included in the final model. These were: substance misuse in the six months prior to release/failure, adjudications in the six months to release/failure; diagnosis (subthreshold traits) of personality disorder; behavioural warnings in the 12 months prior to transfer to open conditions; total adjudications across sentence; and OASys Violence Predictor (OVP) risk assessment score. The magnitude of the effect sizes was determined using Cohen’s (1988) rules and converting these into the corresponding effect sizes outlined in Salgado (2018). Thus, Cohen's d of .2 (small), .5 (medium) and .8 (large) are represented by ORs of 1.434, 2.488 and 4.258, respectively.
Table 3.2

Selection of Variables in Final Regression Model

<table>
<thead>
<tr>
<th>Step 1: Chi square and Kruskal-Wallis tests</th>
</tr>
</thead>
<tbody>
<tr>
<td>Variables excluded</td>
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<tr>
<td>$X^2$</td>
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<td>Age at Case File Review (CFR)</td>
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<table>
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<th>Step 2: Collinearity tests</th>
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<td>$R$</td>
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<tr>
<td>Number of previous convictions</td>
</tr>
<tr>
<td>&quot;</td>
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</tbody>
</table>

| Variables excluded        |
| Number of previous incarcerations |
| Number of different offence types |

<table>
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<tr>
<th>Step 3: Backward logistic regression</th>
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<td>Variables retained</td>
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<tr>
<td>Variable</td>
</tr>
<tr>
<td>$B$</td>
</tr>
<tr>
<td>Substance misuse in six months to outcome</td>
</tr>
<tr>
<td>Adjudications in six months to outcome</td>
</tr>
<tr>
<td>Diagnosis of personality disorder</td>
</tr>
<tr>
<td>Negative diagnosis</td>
</tr>
<tr>
<td>Subthreshold traits</td>
</tr>
<tr>
<td>Positive diagnosis</td>
</tr>
<tr>
<td>Property index offence</td>
</tr>
</tbody>
</table>

<p>| Variables excluded                  |
| Variable                            |
| Score | $p$ | -2ll change |
| Positive behaviour in 12 months prior to transfer to open | 0.02 | .963 | 0.02 |
| Parole violations                    | 0.20 | .889 | 0.20 |
| Highest risk                         | 0.43 | |
| Low                                 | 0.42 | .811 |
| Medium                              | 0.18 | .894 |
| High                                | 0.15 | .696 |
| Number of previous convictions       | 0.08 | .775 | 0.08 |</p>
<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>z-Value</th>
<th>p-Value</th>
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<tbody>
<tr>
<td>Behavioural warnings in 12 months prior to transfer to open</td>
<td>0.36</td>
<td>0.08</td>
<td>19.10</td>
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<tr>
<td>Total adjudications across sentence</td>
<td>0.06</td>
<td>0.03</td>
<td>4.24</td>
<td>0.039</td>
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<tr>
<td>OVP risk assessment score</td>
<td>0.04</td>
<td>0.015</td>
<td>8.20</td>
<td>0.004</td>
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<td>Treatment completion</td>
<td>-0.82</td>
<td>0.462</td>
<td>3.10</td>
<td>0.078</td>
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<td>Positive behaviour in 6 months to release</td>
<td>0.07</td>
<td>0.785</td>
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<tr>
<td>Prior TRF</td>
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<td>0.778</td>
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<td>Sentence type</td>
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<td>0.791</td>
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<td>IPP</td>
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<td>0.982</td>
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<tr>
<td>Life</td>
<td>0.24</td>
<td>0.627</td>
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<tr>
<td>Employed prior to custody</td>
<td>0.14</td>
<td>0.713</td>
<td>0.14</td>
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<tr>
<td>Behavioural warnings in 6 months to release</td>
<td>0.16</td>
<td>0.687</td>
<td>0.16</td>
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<tr>
<td>OGRS score</td>
<td>0.18</td>
<td>0.668</td>
<td>0.18</td>
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<td>Adverse event</td>
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<td>0.526</td>
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<td>0.415</td>
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<td>0.331</td>
<td>0.94</td>
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<tr>
<td>OASys needs</td>
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<tr>
<td>One</td>
<td>0.22</td>
<td>0.638</td>
<td></td>
<td></td>
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<tr>
<td>Two</td>
<td>0.21</td>
<td>0.648</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Three</td>
<td>4.03</td>
<td>0.045</td>
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<td>Four</td>
<td>0.16</td>
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<td>Five</td>
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<td>Six</td>
<td>0.07</td>
<td>0.793</td>
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<tr>
<td>Seven</td>
<td>2.47</td>
<td>0.116</td>
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<td>Eight</td>
<td>0.00</td>
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<tr>
<td>Constant</td>
<td>-3.59</td>
<td>.680</td>
<td>27.82</td>
<td>&lt;.001</td>
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</tr>
<tr>
<td>Nine</td>
<td>1.31</td>
<td>.253</td>
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<tr>
<td>Ten</td>
<td>3.96</td>
<td>.047</td>
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<tr>
<td>History of mental illness</td>
<td>1.16</td>
<td>.282</td>
<td>1.14</td>
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<tr>
<td>Offending career of 7 years or more</td>
<td>1.19</td>
<td>.275</td>
<td>1.20</td>
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**Step 4: Removal of non-statistically significant variables from those retained at Step 3**

<table>
<thead>
<tr>
<th>Variables retained</th>
<th>Variables excluded</th>
</tr>
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<tr>
<td>Substance misuse in six months to outcome</td>
<td>Property index offence</td>
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<tr>
<td>Adjudications in six months to outcome</td>
<td>Treatment completion</td>
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<tr>
<td>Diagnosis of personality disorder</td>
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<tr>
<td>Behavioural warnings in 12 months to open conditions</td>
<td></td>
</tr>
<tr>
<td>Total adjudications</td>
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</tr>
<tr>
<td>OVP risk assessment score</td>
<td></td>
</tr>
</tbody>
</table>
Part two of the data analysis concerned the other failure groups (abscond, TRF, custody failure, and community failure). Given the small number of failures related to each category, the data were analysed using conceptual content analysis (Weber, 1990) to assess the extent to which these groups were an extension of, or indeed diverged from, the security recall group. The purpose of such was to understand, for future analyses, to what extent these groups were homogenous. Each failure was summarised into a case description to code the content analysis; the most ‘typical’ examples of which are presented in the supplemental materials.

**Results**

**Descriptive Statistics**

The majority of the sample graduated successfully from open prison conditions \(n=216; 68.4\%\). One hundred (31.6\%) individuals ‘failed’. Three (0.9\%) of the total sample \((N=316)\) re-offended whilst resident in open conditions, four (1.3\%) absconded and ten (3.2\%) breached the terms of their licence whilst on temporary release. The remaining and most significant proportion of failures in open conditions were ‘security recalls’ \((n=83; 26.3\%);\) recalls initiated by the prison. The failure event in open conditions typically occurred after 357 days on average \((\text{range}: 55\text{-}1735)\) with absconds typically occurring earlier \((M_{\text{days}} = 272)\) and temporary release failures (TRFs) occurring later \((M_{\text{days}} = 443)\).

Table 3.3 provides an overview – of those men released from custody during the following up period – of the community recall and re-offending rates for each of the groups outlined above. Manifestly, all successful open prison graduates were released \((n=216)\), with six (2.8\%) re-offenders and 18 recalls (8.3%). Eighty-three of
the 100 men who failed in open conditions were released during the following period.

Nine re-offended (10.8%) and 16 were recalled (19.3%).

Table 3.3

Numbers and Proportions of Released Prisoners Reoffending / Recalled within One Year

<table>
<thead>
<tr>
<th>Year</th>
<th>Community recall</th>
<th>Community recidivism</th>
</tr>
</thead>
<tbody>
<tr>
<td>Successful open prison graduates (n = 216; 68.4%)</td>
<td>18/216 (8.3%)</td>
<td>6/216 (2.8%)</td>
</tr>
<tr>
<td>Absconds (n = 4; 1.3%)</td>
<td>1/3 (33.3%)</td>
<td>0/3 (0.0%)</td>
</tr>
<tr>
<td>Custodial re-offences (n = 3; 0.9%)</td>
<td>0/1 (0.0%)</td>
<td>0/1 (0.0%)</td>
</tr>
<tr>
<td>Release Failures (TRFs) (n = 10; 3.2%)</td>
<td>2/6 (33.3%)</td>
<td>2/6 (33.3%)</td>
</tr>
<tr>
<td>Security recalls (n = 83; 26.3%)</td>
<td>13/72 (18.1%)</td>
<td>7/72 (9.7%)</td>
</tr>
<tr>
<td>Total failures (n = 100; 31.6%)</td>
<td>16/83 (19.3%)</td>
<td>9/83 (10.8%)</td>
</tr>
</tbody>
</table>

Note. Some prisoners were not released to the community during the follow-up period accounting for the differences between the number of failures in the first column and the denominators in the second two columns.

Model of Security Recall

A logistic regression analysis was used to assess which of the six independent variables accounted for unique variance in predicting recall to prison for security reasons. The final model is presented in Table 3.4.

Three variables produced large effect sizes. Substance misuse in the six months to recidivism/failure was the best predictor, increasing the odds of recall by a factor of 17.46 (95%CI: 5.99, 50.89). Each additional adjudication in the six months to recidivism/failure increased the odds of recall by a factor of 10.63 (95%CI: 4.21, 26.85). Personality disorder also predicted recall – albeit only those formally assessed as having problematic personality traits subthreshold for diagnosis were more likely to be recalled (OR = 5.20, 95%CI = 2.01, 13.46). Likewise, each additional behavioural warning in the 12 months to transfer to open conditions (OR = 1.42, 95%CI = 1.21,
1.67) and each unit increase in the OVP score (OR = 1.05, 95%CI = 1.03, 1.08) increased the odds of recall; both small effect sizes. Total number of adjudications across sentence was not a significant predictor and was dropped from the final model. Overall, the model accounted for 57% of the variance and correctly classified 85% of the sample (No recall = 93.8%; Recall = 62.7).

Table 3.4

*Logistic Regression Model for Prediction of Security Recalls*

<table>
<thead>
<tr>
<th>Variable</th>
<th>β</th>
<th>S.E.</th>
<th>Wald</th>
<th>p</th>
<th>Exp(β)</th>
<th>CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Substance misuse in six months to recidivism/failure</td>
<td>2.86</td>
<td>0.55</td>
<td>27.45</td>
<td>&lt;.001</td>
<td>17.46</td>
<td>[5.99, 50.89]</td>
</tr>
<tr>
<td>Adjudications in six months to recidivism/failure</td>
<td>2.36</td>
<td>0.47</td>
<td>25.04</td>
<td>&lt;.001</td>
<td>10.63</td>
<td>[4.21, 26.85]</td>
</tr>
<tr>
<td>Diagnosis of personality disorder</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>14.38</td>
<td>.002</td>
</tr>
<tr>
<td>Negative diagnosis</td>
<td>-0.47</td>
<td>0.52</td>
<td>0.81</td>
<td>.369</td>
<td>0.63</td>
<td>[0.23, 1.67]</td>
</tr>
<tr>
<td>Subthreshold traits</td>
<td>1.65</td>
<td>0.47</td>
<td>11.54</td>
<td>.001</td>
<td>5.20</td>
<td>[2.01, 13.46]</td>
</tr>
<tr>
<td>Positive diagnosis</td>
<td>0.39</td>
<td>0.60</td>
<td>0.43</td>
<td>.510</td>
<td>1.48</td>
<td>[0.46, 4.78]</td>
</tr>
<tr>
<td>Behavioural warnings in 12 months to transfer to open</td>
<td>0.35</td>
<td>0.82</td>
<td>18.45</td>
<td>&lt;.001</td>
<td>1.42</td>
<td>[1.21, 1.67]</td>
</tr>
<tr>
<td>OASys Violence Predictor (OVP)</td>
<td>0.05</td>
<td>0.14</td>
<td>14.03</td>
<td>&lt;.001</td>
<td>1.05</td>
<td>[1.03, 1.08]</td>
</tr>
<tr>
<td>Total adjudications across sentence</td>
<td>0.05</td>
<td>0.03</td>
<td>3.10</td>
<td>.078</td>
<td>1.05</td>
<td>[0.99, 1.16]</td>
</tr>
<tr>
<td>Constant</td>
<td>-4.16</td>
<td>0.55</td>
<td>56.46</td>
<td>&lt;.001</td>
<td>0.16</td>
<td></td>
</tr>
</tbody>
</table>

Cox and Snell = 0.40; Nagelkerke $R^2 = 0.57; -2 \log \text{likelihood} = 200.046; \text{Correctly classified} = 85.0% 

Table 3.5 provides a breakdown of the mean scores for the security recall group versus those who were successful in open conditions and on release according to the five predictive independent variables included in the final logistic regression model.
Table 3.5

Security Recall Versus Non-Failures According to the Five Independent Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Total (N=293)</th>
<th>No recall (N=210)</th>
<th>Recall (N=83)</th>
<th>Statistic/Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Adjudications in six months to recidivism/failure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M (SD)</td>
<td>0.2 (0.4)</td>
<td>0.1 (0.2)</td>
<td>0.4 (0.6)</td>
<td>$X_{(1)}^2 = 44.00$</td>
</tr>
<tr>
<td>Median</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>Behavioural warnings in 12 months to transfer to open</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M (SD)</td>
<td>1.4 (2.0)</td>
<td>1.0 (1.7)</td>
<td>2.5 (2.4)</td>
<td>$X_{(1)}^2 = 51.38$</td>
</tr>
<tr>
<td>Median</td>
<td>1</td>
<td>0</td>
<td>2</td>
<td>$p &lt; 0.01$</td>
</tr>
<tr>
<td>Diagnosis of personality disorder</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not assessed</td>
<td>168</td>
<td>126</td>
<td>42</td>
<td></td>
</tr>
<tr>
<td>Negative diagnosis</td>
<td>58</td>
<td>47</td>
<td>11</td>
<td>$X_{(1)}^2 = 11.80$</td>
</tr>
<tr>
<td>Subthreshold traits</td>
<td>45</td>
<td>25</td>
<td>20</td>
<td>$p = 0.01$</td>
</tr>
<tr>
<td>Positive diagnosis</td>
<td>24</td>
<td>14</td>
<td>10</td>
<td></td>
</tr>
<tr>
<td>OASys Violence Predictor (OVP)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M (SD)</td>
<td>23.1 (13.5)</td>
<td>20.7 (12.4)</td>
<td>29.1 (14.4)</td>
<td>$X_{(1)}^2 = 56.76$</td>
</tr>
<tr>
<td>Median</td>
<td>21</td>
<td>19</td>
<td>27</td>
<td>$p = 0.13$</td>
</tr>
<tr>
<td>Substance misuse in six months to recidivism/failure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>No</td>
<td>254</td>
<td>206</td>
<td>48</td>
<td>$X_{(1)}^2 = 76.39$</td>
</tr>
<tr>
<td>Yes</td>
<td>41</td>
<td>6</td>
<td>35</td>
<td>$p &lt; 0.01$</td>
</tr>
</tbody>
</table>

The mean scores and standard deviations were used to produce cut-off scores to distinguish the security recall group from the non-recall group, on each variable. Where there was overlap in the standard deviation of the means, 99% confidence intervals were applied to select the cut-off score. The mean number of items observed for the security recall group was calculated and compared against the other failure groups (abscond, reoffending, TRF) to identify the extent to which these groups
could be considered an extension of the security recall group. These cut-off scores are outlined in Table 3.6.

**Table 3.6**

*Security Recall Cut-Off Scores*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Non-recall</th>
<th>Security recall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Substance misuse in last six months</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Number of adjudications in six months to outcome</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Personality disorder diagnosis</td>
<td>Not assessed / negative diagnosis</td>
<td>Subthreshold traits</td>
</tr>
<tr>
<td>Behavioural warnings in 12 months to open conditions</td>
<td>0-1</td>
<td>2+</td>
</tr>
<tr>
<td>OASys Violence Predictor (OVP) score</td>
<td>0-23</td>
<td>24-100</td>
</tr>
</tbody>
</table>

Only one case in the security recall group met the criteria for every variable. On average, they met the criteria for two of the five variables ($M = 2.23; SD = 0.99$).

**Case Descriptions**

Below I briefly summarise case descriptions of the ‘rare event’ groups. Their similarities/differences were compared to the security recall group to assess the extent to which these groups were an extension of, or indeed diverged from, the security recall group. Fuller descriptions of cases ‘typical’ to each category is available in the supplemental material.

**Absconders**

Four individuals absconded from open conditions. On average they met the criteria for fewer than one of the five ‘security recall’ variables ($M = 0.75, SD = 0.96$). Three individuals were serving indeterminate sentences and three had been recalled to custody at least once during the sentence following release. Despite this, three of the four individuals were assessed as a low risk for re-offending and in the three cases
where details of the abscond were investigated, all three reported relational problems with peers in the prison, acting as a catalyst to the abscond.

**Temporary Release Failures (TRFs)**

Ten individuals breached their licence whilst in the community on Release on Temporary Licence (RoTL). On average, they endorsed one of the variables predictive of security recall ($M = 1.40; SD = 1.07$). All except one were serving indeterminate sentences. All individuals had accessed structured treatment to address their offending behaviour, and the majority (seven) were assessed as a low risk of re-offending. Nonetheless, all attracted behavioural warnings in the six months prior to the TRF. In most cases, the TRFs related to institutional offence behaviour such as misuse of substances, or engagement in sexually inappropriate behaviour/relationships.

**Custody Re-offenders**

Three individuals were reconvicted whilst resident in open conditions. On average they met the criteria for less than two of the variables associated with the security recall group ($M = 1.67; SD = 1.15$). All were serving indeterminate sentences. Drawing patterns from the data is difficult given two of the three individuals were convicted for bringing unauthorised mobile phones into a prison. This is an indictable offence in England and Wales but arguably might be better framed as a breach of licence. These prisoners were also younger (age < 30) than the security recall group and claimed to have been extorted or influenced by peers.

**Community Re-offenders**

Six individuals, released from open prisons, were reconvicted within one year of release to the community. On average, they endorsed one or two variables predictive of security recall ($M = 1.50; SD = 1.05$). All six had offence histories
spanning seven years or more, were serving indeterminate sentences and had a
history of substance misuse, reflecting a history of antisocial behaviour. The age
range (31-45 years) was relatively narrow. All were considered to have completed
treatment commensurate with their re-offending risk yet all but one had attracted a
behavioural warning of some form in the six months prior to release to the
community.

Discussion

The primary aim of the present study was to isolate a set of factors predictive
of increased risk of failure in open prisons. Scant previous research has examined risk
factors for custodial release failure yet such understanding is crucial, not only for the
effective management of risk but also for maintaining the legitimacy of open prisons
and in particular, temporary release schemes, given their positive impact on
recidivism rates (Cheliotis, 2008; Hillier & Mews, 2018; Ministry of Justice, 2015,
2019).

Sufficient data were available to statistically isolate factors predictive of
‘security recall’, and three factors produced large effect sizes. Subthreshold traits of
personality disorder (large effect), each additional unit increase in OASys Violence
Predictor (OVP) score, and each additional behavioural warning in the 12 months prior
to transfer to open (both small effects), are each measurable prior to receiving
prisoners in open conditions and so could be used to pre-emptively assign cases to
EBM. Substance misuse and each additional unit increase in adjudications in the six
months prior to recall produced large effect sizes, highlighting the importance - in
predicting adverse outcomes - of continuously monitoring behaviour (Clark et al.,
1993; McDougall et al., 2013). On average, these behavioural indicators of risk
typically emerged at one year (357 days) from transfer to open conditions and could be used to *reactively* assign prisoners to EBM.

The factors predictive of security recall are shown consistently to predict recidivism and are accounted for by Bonta and Andrews’ (2017) General Personality and Cognitive Social Learning (GPSCL) theory. The number of institutional infractions (measured here by adjudications in the six months to failure and behavioural warnings in the 12 months to transfer to open conditions) is likely a marker of antisocial persistence (Andrews et al., 2006; Bonta & Andrews, 2017) given behavioural schemas are relatively stable across time and context (Mischel & Shoda, 1995) and act frequency (i.e., repeated acts of antisocial behaviour) provides a reliable index of antisocial persistence (Buss & Craik, 1983). Notably, behavioural warnings in the six months prior to recall did not feature in the final model. Open prisons operate with a smaller staffing model than closed prisons, so it is plausible that antisocial behaviours go undetected more frequently, and it is only those observed behaviours of sufficient severity to warrant adjudication, which correlate with recall. It is also possible that a timeframe of six months was insufficient to tap into antisocial persistence.

Antisocial personality is one of the ‘big four’ risk factors for recidivism and in this study, personality disorder diagnosis predicted recall. Still, it was those with *subthreshold* traits of personality disorder who were more likely to be recalled. There are several possible hypotheses to explain the lack of relationship between diagnosed personality disorder and security recall. First, the variable captured any form of personality diagnosis, not just those with antisocial orientation and thus included diagnoses which do not correlate strongly with re-offending (cf. Roberts & Coid, 2010) diluting the relationship. Yet, Burt and colleagues (2016) found that even in highly psychopathic offenders, re-offending rates can be moderated by factors such as age,
the presence or absence of particular traits, and level of community support. Given subthreshold traits of personality disorder did predict security recall, another perhaps more plausible hypothesis is that those with diagnoses of personality disorder were screened into and received more intensive rehabilitative intervention (cf. Skett et al., 2017). That is, these individuals were either rehabilitated, i.e., ‘walking the walk’, or had learned at least, how to ‘talk the talk’. Substance misuse also significantly predicted recall and represents one of the ‘moderate four’ risk factors for criminal recidivism (Andrews et al., 2006; Bonta & Andrews, 2017).

The final factor – OVP score – is potentially anomalous within the GPSCL theory. Whilst the OVP has predictive validity for violent offending (Howard & Dixon, 2012; 2013), meta-analyses consistently find that a history of violent offending is less predictive of recidivism compared to other offence types, particularly burglary (Goodley et al., 2022). Furthermore, having a violent conviction did not predict failure in the current sample. However, the OVP does tap into stable dynamic risk factors consistent with the GPCSL theory (e.g., attitudes, employment), perhaps accounting for unique variance in the model.

There were notable omissions from the final model predicting security recall. Neither prior abscond nor TRF correlated with security recall despite predicting abscond elsewhere (Mews, 2014). However, the numbers of men with such histories were too low to draw firm conclusions in this study. Likewise, there was no identifiable link between security recall and the ‘push’ and ‘pull’ factors described in qualitative studies of open prison failure (Berman-Roberts, 2015; Chant, 2015; Flowers, 2014; Papworth, 2015; Picksley, 2016; Roberts, 2016). Atkinson and Mann (2012) describe a number of procedural and individual level reasons why important risk-related information such as these ‘push’ and ‘pull’ factors goes unrecorded by
staff which might be further exacerbated in open prisons given their lower staffing profile compared to closed prisons. Finally, factors which consistently predict re-offending such as age, criminal history (i.e., previous convictions, incarcerations) and some measures of antisocial persistence (e.g., offending history length, offence versatility) did not correlate with security recall. Since Eno-Louden and Skeem (2013) have previously identified the prevalence of bias in the recall decisions of community probation officers, assessing the basis for decision-making amongst open prison managers is worthy of exploration.

**Does Failure in Open Conditions Equate to Later Community Re-offending?**

A secondary aim of this study was to explore whether failure in open conditions equates to later community re-offending and to consider whether wraparound support packages in open prisons, like EBM, should always be targeted at those who infringe custodial rules. The present study found that whilst open prison graduates re-offended at the lowest rates (2.8%), there was, nonetheless, a mismatch between the number of men being returned to closed prisons for security reasons ($n=72$) and their community re-offending rates ($n=7$). Violations inevitably create methodological and policy-level challenges (see Ostermann et al., 2020 for a discussion). Returning a prisoner to closed conditions prevents the re-offending outcome from being determined; all or none of these individuals might have been on a re-offending pathway. Relatedly, returning the individual to closed conditions represents an intervention that might change the trajectory of offending.

Whilst determining the effectiveness of security recall as an intervention is beyond the scope of this paper, some conclusions can be drawn from the current data and wider literature. First, those who utilise resettlement opportunities afforded by temporary release schemes in open prisons, are less likely to re-offend (e.g., Cheliotis,
They re-offend at lower rates compared to closed custodial samples (Ministry of Justice, 2019) and in the present study, open prison failures. Second, the current data suggest that the sensitivity of decision-making in open conditions is effective. Arguably, only 17 adverse events – three custodial re-offences, four absconds and ten release failures - were missed. Yet, to achieve that sensitivity, there is a trade-off with specificity. Over 90% of those returned to closed conditions for security reasons did not re-offend in one year of release. Given the best interventions reduce recidivism by 40% (Lipsey & Wilson, 1998) and meta-analyses indicate that discipline-based approaches delivered without rehabilitative support are unlikely to reduce re-offending (Barnett & Howard, 2018), I contest that prisoners are too readily being recalled. The research indicates that factors such as positive punishment (Schaefer, 2016), procedural injustice (Beijersbergen et al., 2016), stigma and lack of hope (LeBel et al., 2008) all associate with re-offending. Therefore, alternatives to recall are likely to be less costly both psychologically and financially, as discussed below.

**EBM and Rare Event Outcomes**

Statistically, there was little difference between the profiles of the security recall and other failure groups. Whilst those falling into the other failure groups endorsed fewer variables predictive of security recall on average, this difference was not significant indicating that custodial rule infringement (i.e., adjudications, behavioural warnings, substance misuse) may be relevant to preventing other adverse outcomes. Nonetheless, it was tentatively possible to isolate patterns of behaviour in the qualitative data, specific to each failure group, providing direction for further research. For instance, three of the four absconders were serving indeterminate sentences, three had previously been recalled to custody during the current sentence, and three reported relational problems in the prison (e.g., bullying). These patterns
mirror both the loss of hope observed in those serving IPP sentences – particularly those recalled to custody (Beedon, 2020; Harris et al., 2020; Merola, 2015) and the ‘push’ factors reported in custodial absconder samples (e.g., Picksley, 2016). Serving an indeterminate sentence was also a consistent feature amongst those who failed on temporary release and re-offended whilst in custody perhaps also reflecting dangerousness and antisocial persistence amongst IPP prisoners. It is also noteworthy that those who breached the terms of their temporary release had done so by engaging in offence-related behaviour, attracting behavioural warnings in the six months prior to the breach. Pearson and McDougall (2017) discuss the important contribution to risk evaluations that can be made by aggregating ‘lower level’ prison behaviours such as insults, threats, and bullying.

Given the limitations of the data and the relative frequency with which some of these variables are observed in the population (e.g., IPP sentences), it would be neither practicable nor cost-effective to target wraparound support packages, such as EBM, to all prisoners with the characteristics observed in the abscond, temporary release failure (TRF), and custodial re-offending groups. Nonetheless, the data highlight the value of monitoring and attending to behaviours displayed by prisoners in open conditions, particularly those serving IPP sentences and those recalled to custody. Likewise, adverse outcomes such as abscond and re-offending whilst resident in custody in England and Wales, are rare events; ensuring temporary release is purposeful and based upon a current assessment of risk has likely impacted rates of failure (cf. HM Inspectorate of Prisons, 2014; Simpson et al., 2015). Consequently, there is a degree of futility in trying to predict serious recidivistic events in open conditions based on individual-level factors only, without producing excessive false positive errors and either recalling, or providing costly support services to, a sizeable
proportion of individuals who would not otherwise have failed in open conditions.

Beyond effective risk management, rates of abscond and re-offending in open prisons can likely be lowered by addressing the ‘push-pull’ factors previously described (e.g., Picksley, 2016); good relational security (good-staff prisoner relationships) (Mezey et al., 2015) and developing rehabilitative cultures (Auty & Liebling, 2020).

**Practical Implications**

The present findings could be practically applied in a number of ways. First, the criteria used to predict security recall could be used to distinguish between those at greater risk of failure in open conditions compare to those at lower risk. Given the model was relatively more effective at identifying non-recalls (93.8%) than recalls (62.7%), the criteria could be most usefully applied to identify those who are *unlikely* to require additional support in open conditions, with any resource efficiencies being diverted into interventions for those exhibiting indicators of risk-related behavioural deterioration. Indeed, adverse outcomes typically occurred after 357-days on average. As such, the decision to trigger wraparound support packages to those at greater risk of recall could reasonably be deferred until there are behavioural indications related to one of the stronger proximal predictors of recall (i.e., substance misuse; behavioural warnings, particularly adjudications). This study also provided tentative evidence that behavioural deterioration in particular groups (e.g., indeterminate sentence prisoners, recalled prisoners) is potentially indicative of raised risk of more serious adverse outcomes (i.e., abscond, reoffending), with wraparound support packages providing the scaffolding needed to aid behavioural stabilisation. However, this was based on a qualitative analysis of a small sample of serious recidivistic failures and further research is required to establish the veracity of these conclusions.
Arguably this paper lifts the lid on more systemic problems in open prisons in England and Wales, the learning from which is applicable to open prisons internationally. In our sample, almost one-third of prisoners transferred to open conditions ‘failed’ and of those prisoners recalled to closed conditions, 90% did not re-offend in the first year of release. There was overreliance on a costly system of dealing with risk-related behaviour, perhaps reflecting a decision-making bias which has been observed amongst related staff groups (Eno-Louden & Skeem, 2013). Further research is required and where evidence exists, training to help staff correctly identify behaviours indicative of an increase in risk is indicated (cf. Clark et al., 1993; McDougall et al., 2013). Building secure accommodation on open prisons sites might also, potentially, afford prison managers time to adequately investigate aberrations before initiating recalls. Yet, the high number of recalls might justifiably reflect the serious political implications that adverse events can have on the legitimacy of an institution (cf. Dawar & Davis, 2014; HM Inspectorate of Prisons, 2014). Open prisons in England and Wales have little control over who is recategorised and inappropriate recategorisations may translate to risk aversion. A review of the recategorisation process in England and Wales is warranted. Open prisons should have decision-making powers in recategorisation assessments whilst other bodies involved (e.g., closed prisons, Parole Boards) should be made accountable for understanding the managed risks in open conditions and justifying their decision-making. Integrating open prison sites into closed prisons might also improve selection and preparation of prisoners.

Conclusions

The current study contributes to understanding, predicting, and mitigating the risk of serious failure outcomes in open prisons. The evidence indicates that open
prisons, and in particular temporary release schemes, positively impact on recidivism (e.g., Cheliotis, 2008) and arguably, in the pursuit of successfully resettling high-risk prisoners back in their communities, should be an essential component of prison systems globally. Failures inevitably undermine the legitimacy of such institutions but as demonstrated, many failures occur following observable behavioural indicators of risk-elevation. Therefore, behavioural monitoring interventions such as EBM or equivalent initiatives are likely to have utility and some precision in detecting whom would benefit from a package of support; as well as informing post-release licence conditions (McDougall et al., 2013). Serious failure outcomes were few in the current study perhaps reflecting that the adoption of clear risk assessment protocols, particularly around temporary release, is sufficient to mitigate risk (HM Inspectorate of Prisons, 2014; Simpson et al., 2015). Indeed, predicting serious adverse outcomes (e.g., abscond, re-offending) based upon static factors was futile given the limited variability within the population (e.g., all high-risk offenders) and low base rates for such events, prompting our call for open prisons to focus upon relational security and rehabilitative cultures to identify and mitigate the potential ‘push-pull’ factors underpinning these events. Managing the risk cynically through transferring prisoners back to closed conditions is potentially iatrogenic (cf. Alexander, 2006) and at the very least, in our study, was a costly intervention that correlated poorly with community recidivism outcomes.

Notes

1 The name/number of the prisoner on the EBM database could not be reliably matched to an electronic file.

2 It was necessary to convert some risk categories based on the difference in known re-offending rates (e.g., lower rates of sexual recidivism vs. violent recidivism). I took the sexual re-offending rates associated to the Risk Matrix 2000 (RM2000) risk categories in Barnett and colleagues (2010) and
superimposed these onto the risk categories and associated re-offending rates of the OASys Violence Predictor (OVP) tool in Howard and Dixon (2012). Those rated as low and medium risk for sexual recidivism on the RM2000 corresponded to the re-offending rates of those assessed as low risk on the OVP and as such, were classified as ‘low’ risk. Those rated as high and very high risk on the RM2000 corresponded to the re-offending rates of those assessed as medium risk on the OVP and were classified as ‘medium risk’.
Appendix

In the published article, the four case descriptions below were included as supplementary material.

A. Abscond Case Description - Graeme

Graeme, 58 years old, had been resident in open conditions for 506 days prior to absconding. He had four previous convictions but was serving his first custodial sentence - a life sentence – for the murder of a child. He had been released to the community twice during the sentence only to be recalled on both occasions due to alcohol consumption, associating with pro-criminal peers and latterly, assaulting another male. He had previous diagnoses of borderline personality disorder and depression. He was assessed as a medium risk (40) for further violence on the OASys Violence Predictor (OVP). His official custodial behaviour was largely unremarkable. He was variously described as quiet, polite, and compliant, rarely coming to the attention of staff. He had no adjudications against him in custody. In the year prior to moving to open conditions he lost his mother but seemingly processed his loss appropriately and remained focused on his sentence plan. His time in open conditions was also largely unremarkable, although in the weeks prior to the abscond, his wing behaviour record details a deterioration in his health. Graeme has pre-existing medical conditions affecting his mobility. The deterioration resulted in an enforced accommodation move away from the semi-independent resettlement unit for medical assistance. There was also a late change to his hostel placement due to bed space availability in the days before his RoTL; the same RoTL of his absconsion. Graeme
cited as the catalyst ‘intimidation’ and ‘bullying’ by other residents following the prison accommodation move. Crucially, this information was either not known to, or not recorded by staff.

B. Temporary Release Failure (TRF) Case Description - Rob

Rob, aged 55, was resident in open conditions for 580 days at the time of his TRF. He had nine previous convictions, mainly for acquisitive offences but also an emerging pattern of sexual offending behaviour. He was serving a life sentence – his first custodial sentence - for three rapes, one of which was a historical offence. The attacks were against lone females, unknown to Rob, and occurred at night. They occurred following rejection and were underpinned by a sense of sexual entitlement and an interest in sexual violence. He was diagnosed as having traits of antisocial personality disorder, subthreshold for a definitive diagnosis. Rob was initially released to the community in 2004 but was recalled for associating with ex-offenders and forming relationships with two vulnerable women, breaching his licence. He was tried for rape of an ex-partner but not convicted. Rob denied the rape but admitted to being sexually promiscuous and drinking heavily on licence. He worked his way back through the prison system to open conditions; his good behaviour and engagement with structured programmes to address his sexual offending, underpinning the Parole Board’s decision. Nonetheless, there remained professional disagreement over his failure to complete treatment specifically addressing his sexual interest in violence. Rob’s time in open conditions was unremarkable. There were minor breaches of the rules initially (being in possession of DVD that was not his; visiting his friend on RoTL without permission) but not in the six months to the failure. Rob was recalled to closed conditions when police raided a property where he was
present during an overnight RoTL in his release area. He was not permitted to be there. Moreover, he was at the property with another ex-offender (sexual convictions) and found in state of undress, in the presence of two sex workers.

C. Custody Re-offender Case Description - Harry

Harry, aged 49, had been resident in open conditions for 325 days prior to re-offending. He has a history of serious offending – mainly burglaries – including weapon use. Indeed, he had served eight custodial sentences from nine of his previous convictions. He has one previous conviction for rape. The index offence of wounding with intent to cause GBH occurred in a public house in which he assaulted another male with a weapon, resulting in a life sentence. His offending was predominantly underpinned by his substance use. He has a diagnosis of antisocial personality disorder, and this manifested in custody as he accrued 34 adjudications over the course of his sentence, mainly during the initial years. He did not accrue any adjudications in the year prior to transfer to open conditions albeit he received five behavioural warnings from staff, mainly relating to his work ethic/attendance. This pattern continued into open conditions with a handful of warnings for aggressive outbursts towards both staff and other prisoners. Harry was convicted of sexual assault, touching the female victim in a sexually inappropriate way. The victim was not known to Harry; she was another patient in the hospital where he was undergoing investigations. Harry had recently been diagnosed with cancer. He describes having a nervous breakdown at the time. Whilst he denies the offence, professionals’ postulate that he was unable to cope with the news and the offence was a form of self-soothing.
D. Community Re-offender Case Description - Les

Les, aged 31, had been released to the community for 339 days prior to re-offending. He has a history of violent behaviour (robbery and violent assaults); he has six previous convictions and has served four previous custodial offences. Within the index offence he threatened one victim with a knife after the victim had spoken to his girlfriend and stabbed another victim a few days later in a dispute over a drugs debt. He has a history of substance misuse. Les was assessed as a medium risk (32) for further violence on the OASys Violence Predictor (OVP). During his early prison sentence, he attracted three adjudications for fighting mainly but his behaviour became more settled over time and following completion of structured programmes to address his substance misuse and violence risk. His behaviour was relatively unremarkable prior to transferring to open conditions although he was warned for some low-level rule breaches during his time in open conditions, associated with lateness and trying to circumvent systems by presenting incorrect paperwork. Les was convicted when he was stopped in his car. He was in possession of a gun, ten wraps of cocaine, and £225 pounds in cash. Drug paraphernalia was found at his home address. Les admitted that he had slipped into his previous lifestyle after reacquainting with his old friendship group.
Chapter 4: Evaluation of an Enhanced Behaviour Monitoring System in UK Open Prisons

A manuscript based on this chapter was submitted for publication and is currently under review.

Chapter 4: Evaluation of an Enhanced Behaviour Monitoring System in UK Open Prisons

Abstract

Behavioural monitoring has efficacy in predicting recidivism but as an intervention the proven effectiveness of such schemes is limited. The present study is an evaluation of the Enhanced Behaviour Monitoring (EBM) scheme, implemented in open prisons in England and Wales, to reduce instances of failure (e.g., abscond, reoffending). Using both an intention to treat (ITT) and treatment received (TR) approach with a sample of adult male prisoners matched to a control group, logistic regression analyses showed that EBM had null effects on serious recidivistic outcomes (e.g., abscond, reoffending). Those allocated to EBM were more likely to get recalled before completing the intervention, per-protocol. The chapter reviews the findings in the context of limitations within the matching strategy and discusses the rehabilitative potential within EBM given the lessons learned from the intensive supervision.

Keywords

Abscond; Behavioural Monitoring; Open prisons; Recidivism; Risk management; Temporary Release Failure

Introduction

The presumptions underlying the most commonly used forensic risk assessment tools are majority biased and result in the misclassification of a significant proportion of offenders (Eckhouse et al., 2019; Monahan et al., 2017). Eckhouse and colleagues (2019) argued that data-driven risk prediction tools are rarely individualised to the
offender and assessments utilising group-based averages discriminate against certain groups. One group where the risk of recidivism is often overestimated is older offenders (Monahan et al., 2017), such that the accurate assessment of those serving lengthy indeterminate sentences for serious offences has been considered a long-standing problem for criminal justice systems (cf. Clark et al., 1993). Conversely, risk underestimation is common in some groups, such as a subset of offenders with limited criminal histories who later go on to commit homicide (Greenall & Richardson, 2015; Soothill et al., 2002). It is these latter cases which, particularly where a further offence is the outcome, have the most damaging consequences, causing public outrage, and increased scrutiny of those organisations managing the risk (cf. Dawar & Davis, 2014).

Whilst some academics argue that forensic risk assessment – a *prognostic* task - should not be held to the evaluative standards of *diagnostic* assessments which seek to identify a condition that already exists (Helmus & Babchisin, 2017), others propose behavioural monitoring as a promising means of individualising risk assessment, contemporaneously forecasting reoffending probability, and optimising risk management (Clark et al., 1993; Goodley et al., 2022; Jones, 2004; Pearson & McDougall, 2017). In a behavioural scheme, it is possible to identify behaviour patterns at the time of offending and make risk judgements based on the present ‘flow of behaviour’ (Jones, 2000). The review below suggests behavioural monitoring protocols have the potential to structure professional judgements of risk and monitor progress at a more nuanced level, thereby facilitating intervention following the observation of risk-related behaviour. This article presents an evaluation of a behavioural monitoring protocol – Enhanced Behaviour Monitoring (EBM) (NOMS, 2015) – implemented nationally across open prisons in England and Wales since 2015.
The Utility of Behaviour Monitoring

Behavioural monitoring has the potential to overcome some of the systematic constraints observed in forensic risk assessment, such as the misclassification of risk due to time/resource restrictions (Ho et al., 2018; Vogt et al., 2013). By their very nature, dynamic risk assessments have short-term validity, necessitating regular review. Yet the administration of Structured Professional Judgment (SPJ) tools is time-consuming (Green et al., 2010); the accurate discrimination of case-relevant factors is impeded by operational time constraints resulting, arguably, in flawed decision-making (Ho et al., 2018). In the absence of regular review, limitations also emerge in the way risk factors are measured and evaluated. Jones (2004) argues that conventional risk assessment protocols often result in risk predictions based on past, discrete episodes of behaviour. Harris and Rice (2015) assert that dynamic risk factors become static in nature when measured once: the dynamic risk information – the very aspect that makes the risk factor changeable (Douglas & Skeem, 2005) – becomes lost. In contrast, behavioural consistency can be measured more accurately and effectively, over both time and context, using a behaviour monitoring scheme (Clark et al., 1993; McDougall et al., 2013; Pearson & McDougall, 2017).

Behavioural monitoring systems necessitate staff training in the identification of risk-related behaviour and are premised on effective inter-agency communication. As such, there is scope to delve deeper than official, often incomplete, information sources (cf. McDougall et al., 2013; Pearson & McDougall, 2017). Institutional misconduct offences – as an official risk information source – provides a case in point. ‘Situational muting’ (Daffern et al., 2007) – the suppression, by the prison environment, of the prototypical precipitants of the offending behaviour and the
limiting of access to victims/opportunities to offend, might diminish expressions of antisocial behaviour (Gordon & Wong, 2010; Jones, 2004). Likewise, some institutional infractions simply go unrecorded in wing behaviour records rendering official information sources, as an indicator for violence propensity, unreliable (Adams, 1992; Mooney & Daffern, 2015). The official recording of incidents is dependent on the recording threshold of individual members of staff (Bottoms, 1999). Prison officers are the gatekeepers of observed behaviour, but through a combination of normalisation (e.g., desensitisation to violence), procedural (e.g., insufficient time, lack of observable consequences) and individual factors (e.g., concerns about defensibility, failure to recognise the significance of the behaviour), important risk-related information goes unreported (Atkinson & Mann, 2012). By engaging offenders and inter-agency staff in the risk assessment process and tapping into observations of ‘daily prison life’, behaviour monitoring can unlock current risk-related information, inaccessible to other risk assessment methodologies.

**Utilising Behaviour Monitoring Effectively**

Clark and colleagues (1993) were pioneers in creating a simple behaviour monitoring framework applicable to prisons, later known as the Wakefield Behavioural Risk Assessment model (McDougall et al., 1995). Using behavioural analysis techniques, they were able to identify offence-related behaviour similar to the index offence in 60% of prison behaviours. Building on these findings, McDougall and colleagues (2013) developed the ADViSOR methodology to examine the reverse: whether the community behaviour of those offenders at high risk of committing a violent and/or serious sexual offence on release from prison, could be predicted from their custodial behaviour. However, rather than solely assessing consistency between the index offence and prison behaviours as per Clark et al. (1993), they looked at
prison behaviour more holistically, recording positive and negative behaviours not necessarily linked to the index offence nor functionally equivalent. The study also went beyond those behaviours recorded in official records, recruiting specifically trained staff to record any behaviour of concern observed across custodial environments (e.g., workshops, education). They found that the frequencies of concerning behaviours in custody and the community were significantly correlated and that return to custody for re-offence or recall, could be predicted by the frequency of such behaviours observed in custody. Not only was the prediction of recidivism highly accurate (92%), but there was also qualitative similarity in behaviours observed across prison and the community with 80% of behaviours rated as ‘similar’ or ‘very similar’. McDougall and colleagues (2013) argue that the prison environment does not suppress risky behaviour entirely but rather the expression may change; ensuring staff are trained to spot these subtle behavioural nuances is essential to effective risk monitoring.

**Behaviour Monitoring as an Intervention**

The Clark et al. (1993) and McDougall et al. (2013) studies were primarily interested in identifying whether offence-related behaviour is cross-situational but stopped short of considering whether behaviour monitoring, via the collection of personalised risk information, could be used to intervene; to divert individuals from offence-related behaviours. There are, however, studies in existence to suggest that this is worth pursuing. Simpson and colleagues (2015) demonstrated potential to reduce the number of absconding incidents in a secure forensic psychiatric sample purely through policy change, i.e., the adoption of a risk assessment protocol guided by structured professional judgement principles and multidisciplinary decision-making. The abscond rate reduced from 17.8% pre-implementation to 12.0% post-
implementation when release decisions considered risk indicators as outlined in the Historical-Clinical-Risk-20 (HCR-20); when the temporary release was purposeful (i.e., facilitated rehabilitation/reintegration); and when exposure to risk was gradual, with leave increasing in frequency and intensity over time. Tolisano and colleagues (2017), also using a forensic psychiatric sample, demonstrated that it was possible to modify violent behaviour using risk assessment as the starting point for a wrap-around support package. Presenting two case studies, they showed a reduction in instances of aggression and self-injury over time when a behavioural support plan was informed by a functional behavioural analysis (FBA). The FBA enabled the staff team to identify and remove mismatches between the individual’s needs and the environment, coach positive alternative behaviours, and use effective behavioural strategies such as positive reinforcement to influence behaviour change. Similarly, using a risk assessment protocol as the starting point to determine offence-related risk factors, associated skills deficits and environmental triggers, Ward and Bosek (2002) were able to tailor a community-based behavioural risk management plan to a group of adolescent and adult males with developmental disabilities engaging in inappropriate sexual behaviours. Once more, the risk management plan consisted of ensuring application of robust monitoring and supervision systems whilst coaching positive alternative behaviours. None of the 41 individuals in their sample re-offended during the monitoring period.

Whilst the evidence for using behavioural monitoring as the basis for intervention is encouraging, caution is heeded from the intensive supervision literature. Intensive supervision – a form of community supervision employing more frequent contacts and a variety of other mechanisms to increase surveillance and control (Barnes & Hyatt, 2018) – impacts positively on recidivism outcomes only when
supervisory approaches incorporate a therapeutic element or supervisors act as ‘agents of change’ (Bonta et al., 2011; Drake, 2018; Petersilia & Turner, 1990; Taxman, 2008). In the absence of these elements, such approaches are ineffective at reducing crime and may have iatrogenic effects, serving only to detect non-compliant offenders and increase the rate of reincarceration due to technical violation (Drake, 2018; Hyatt & Barnes, 2017; Petersilia & Turner, 1993). Indeed, Paparozi and Gendreau (2005) found that rehabilitation-orientated parole officers who revoked licences sparingly yielded greater reductions in recidivism, including new convictions, compared with law enforcement-orientated parole officers. However, Clear and Latessa (1993) suggest that the pattern may be more nuanced. They found that officer role preference is mediated by the philosophy of the organisation; such that officers, regardless of role preference, were more likely to select supportive tools to manage the risk when in organisations with a rehabilitative philosophy. Data from Chapter 3 above showed that prison managers in open prisons, given the serious implications of adverse events such as abscond and re-offending, take a conservative approach to non-compliance, misaligned to the community re-offending risk. The introduction of a behavioural monitoring intervention presents an opportunity, where implemented appropriately, to redress this balance.

**The Current Study**

The current study aimed to evaluate a behaviour monitoring protocol - Enhanced Behaviour Monitoring (EBM). EBM is a policy framework implemented in 2014 in open prisons across England and Wales to mitigate instances of abscond, temporary release failure, and serious further offending by resident inmates (NOMS 2015). EBM consists of a psychologist-led file review, thus recognising the importance of a detailed and expert analysis of behaviours indicative of risk manifestation, as per
previous studies (Clark et al., 1993; McDougall et al., 2013). The second element – a behaviour monitoring intervention reserved for those deemed at heightened risk for ‘failing’ on temporary release – specifies a formal process for those involved in the offender’s management to observe and share observations related to the individual’s behaviour. Over a period of six once-monthly meetings with the prisoner, the prisoner’s offender manager reviews these observations against a set of behavioural targets, assisting the prisoner to develop self-management strategies to mitigate emerging risks. Upon completion of the six-month period, having gained assurance that behaviour is stabilised, the standard expectation is that the prisoner returns to ordinary prison management. The present evaluation, using a matched sample, set out to examine whether EBM is effective at reducing ‘failure’ rates. It was hypothesised that those subject to the behaviour monitoring intervention would be less likely to ‘fail’ despite the additional monitoring.

**Method**

**Design and Procedure**

A quasi-experimental design was used to evaluate the effectiveness of Enhanced Behavioural Monitoring (EBM) on failure outcomes in a sample of adult male prisoners resident within open prisons within England and Wales. The dataset consisted of 692 prisoners all of whom were eligible for EBM, meeting one or more of the following criteria as per Prison Service Instruction 13/2015 (NOMS, 2015b):

- serving an indeterminate sentence;
- subject to Multi Agency Public Protection Arrangements (MAPPA);
- and/or, assessed as high or very high risk of harm on the Offender Assessment System (OASys) risk assessment tool (Home Office, 2006). All were subject to a case file review between 11 June 2014 and 21 November 2017 with
those deemed at heightened risk for failure being progressed for behaviour monitoring intervention, as described above.

To ensure sufficient numbers of men in the intervention group, data were collected using a purposive sampling method. Allocation to the intervention group was determined by recommendation for management under EBM - akin to an intention to treat (ITT) approach. Of the total dataset (N = 692), 174 prisoners had a formal recommendation for management under EBM. The remaining 518 prisoners were managed under existing protocols and represented the pool of prisoners from which the control group was selected, using the matching procedure described below.

Demographic and offence-related data were collected from data sources including the EBM case file review, EBM database, National Offender Management Information System (NOMIS), and public protection unit database. Data included age, current offence, sentence type, number of previous convictions, personality disorder diagnosis, previous failures in open conditions, past prison behaviour (behaviour in the year prior to transferring to open conditions; total adjudications), recent prison behaviour (substance misuse, adjudications, and adverse events in the last six months), and a current risk assessment score (e.g., OASys Violence Predictor [OVP]).

**Measures**

The outcome against which the EBM and control group were compared was the observation of a ‘failure’ event. A failure was recorded when any of the following were observed: abscond; custodial re-offence; temporary release failure (TRF); or security recall. Abscond was defined as unlawfully gaining liberty for 15 minutes or more without overcoming a physical security restraint. Custodial re-offence was defined as reconviction for any offence, whilst resident in open conditions. TRF was defined as a failure to adhere to any condition included on the individual’s temporary
release licence. Security recalls were recalls to secure conditions, initiated by a prison manager, typically following a breach of the prison rules, deemed indicative of an intolerable increase in the individual’s risk. Data were retrieved from the NOMIS database and cross-referenced against other records to validate the failure. In a small number of cases the custodial failure could not be validated - the decision to fail was clearly overturned within a 28-day period and the individual returned to open conditions. Such cases were not classified as a failure and the follow-up period continued until the point of release or recording of a valid failure. Data pertaining to custodial ‘failure’ and community recidivism were collated in March 2022. All participants had either graduated or ‘failed’ in open conditions at the end of the follow-up period.

**Matching Strategy**

To ensure the control group matched the EBM group as closely as possible, Propensity Score Matching (PSM) (Rosenbaum & Rubin, 1983) was employed. PSM is a quasi-experimental matching technique designed to overcome selection bias when estimating the effect of a given intervention. The possibility of bias occurs because a difference in the outcome between the intervention and control groups may be caused by a factor which predicts assignment to the intervention group rather than the impact of the intervention itself. PSM aims to minimise this bias by accounting for covariates that predict assignment to the intervention group – in this case, failure in open conditions. This is achieved through a process of ‘matching’ individual subjects in the intervention and control groups according to these covariates, achieving ‘balance’ between the two groups (Austin, 2011; Rosenbaum & Rubin, 1983). Through this process of matching, pre-existing differences between the groups can be
minimised meaning any observed differences in outcomes can, with greater certainty, be attributed to the effect of the intervention (Stuart, 2010).

To ensure the EBM and control groups were matched on those covariates that may confound the relationship between the intervention and outcome, broadly, the covariate selection method outlined in Lee and Little (2017) was followed. First, and based on the findings in Chapter 3, those covariates related to the outcome variable, prior to the implementation of EBM, were identified— in this case, failure in open conditions. The research reported in Chapter 3 identified five predictors of failure in open prisons in England and Wales, namely: adjudications in the six months prior to outcome; substance misuse in the six months prior to outcome; behavioural warnings in the one-year prior to transfer to open conditions; personality disorder diagnosis; and OASys Violence Predictor (OVP) score. From this pool of covariates, adjudications and substance misuse in the six months prior to outcome were discarded given they were susceptible to influence by the intervention itself. The three remaining variables were retained as the matching criteria.

The EBM and control groups were matched using nearest neighbour matching. In nearest neighbour matching, an individual in the intervention group is matched to the individual in the control group with the most similar or nearest propensity score (Rosenbaum & Rubin, 1985). Consequently, this method can result in individuals with relatively dissimilar propensity scores being matched. To avoid ‘bad matches’, a caliper distance – a maximal acceptable distance in which propensity scores can be matched was specified. Austin (2011) suggests using a caliper width equal to .2 of the standard deviation of the logit of the propensity score to eliminate approximately 98-99% of the bias caused by measured confounding variables. A corresponding caliper of .04 was imposed on the data. I also employed nearest neighbour matching with
replacement, meaning that individuals could be matched multiple times if their propensity score was within the least distance to more than one individual in the corresponding group (Dehejia & Wahba, 2002). Three members of the intervention group could not be matched to a member of the control group and were removed from the analyses. In total, there were 171 offenders in the intervention group and 171 in the control group. Table 4.1 shows the sample characteristics pre- and post-matching, including the mean scores for the variables upon which the intervention and control groups were matched. Logistic regression analyses confirmed the groups were adequately matched as group membership could not be differentiated based on these variables: Behavioural warnings $\chi^2 (1, N = 342) = 1.30, p = .256$; OVP score $\chi^2 (1, N = 342) = 0.13, p = .717$; Personality disorder diagnosis $\chi^2 (1, N = 342) = 3.46, p = .327$. 

Table 4.1

Sample Characteristics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full sample (N = 692)</th>
<th>EBM group (N = 171)</th>
<th>Control group (unmatched) (N = 518)</th>
<th>Control group (Matched) (N = 171)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, $M_{\text{years}}$ (SD, Range)</td>
<td>39.0 (12.6, 19-81)</td>
<td>37.5 (11.2)</td>
<td>39.6 (13.0)</td>
<td>35.6 (10.7)</td>
</tr>
<tr>
<td>Previous convictions, $M_{\text{number}}$ (SD, Range)</td>
<td>9.7 (10.9, 0-89)</td>
<td>15.0 (14.8)</td>
<td>7.8 (8.6)</td>
<td>13.2 (10.7)</td>
</tr>
<tr>
<td>Index offense (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burglary</td>
<td>5.9</td>
<td>8.3</td>
<td>5.1</td>
<td>9.8</td>
</tr>
<tr>
<td>Drug</td>
<td>2.5</td>
<td>1.2</td>
<td>2.9</td>
<td>2.4</td>
</tr>
<tr>
<td>Fraud</td>
<td>1.0</td>
<td>0.0</td>
<td>1.4</td>
<td>0.0</td>
</tr>
<tr>
<td>Robbery</td>
<td>16.6</td>
<td>23.7</td>
<td>14.3</td>
<td>19.5</td>
</tr>
<tr>
<td>Sexual</td>
<td>29.4</td>
<td>21.9</td>
<td>31.6</td>
<td>20.1</td>
</tr>
<tr>
<td>Violence</td>
<td>38.3</td>
<td>37.3</td>
<td>38.7</td>
<td>41.5</td>
</tr>
<tr>
<td>Other</td>
<td>6.3</td>
<td>7.6</td>
<td>6.0</td>
<td>6.7</td>
</tr>
<tr>
<td>Sentence type (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Determinate</td>
<td>42.5</td>
<td>21.6</td>
<td>49.4</td>
<td>44.4</td>
</tr>
<tr>
<td>Indeterminate for Public Protection</td>
<td>31.6</td>
<td>46.8</td>
<td>26.4</td>
<td>35.7</td>
</tr>
<tr>
<td>Life</td>
<td>25.9</td>
<td>31.6</td>
<td>24.1</td>
<td>19.9</td>
</tr>
<tr>
<td>Behavioural warnings in 12 months prior to transfer to open conditions $M_{\text{number}}$ (SD, Range)</td>
<td>2.1 (3.1, 0-19)</td>
<td>4.1 (3.98)</td>
<td>1.5 (2.3)</td>
<td>3.6 (3.6)</td>
</tr>
<tr>
<td>Personality Disorder Diagnosis</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not assessed</td>
<td>59.2</td>
<td>48.5</td>
<td>62.9</td>
<td>39.8</td>
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<tr>
<td></td>
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<td>------------------------</td>
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</tr>
<tr>
<td>Negative diagnosis</td>
<td>13.0</td>
<td>12.3</td>
<td>13.3</td>
<td>17.0</td>
</tr>
<tr>
<td>Subthreshold traits</td>
<td>19.1</td>
<td>26.3</td>
<td>16.4</td>
<td>31.0</td>
</tr>
<tr>
<td>Positive diagnosis</td>
<td>8.7</td>
<td>12.9</td>
<td>7.3</td>
<td>12.3</td>
</tr>
<tr>
<td>OASys Violence Predictor (OVP) score $M_{number}$ ($SD, Range$)</td>
<td>26.7 ($15.9, 2-85$)</td>
<td>34.6 ($15.5$)</td>
<td>23.9 ($15.0$)</td>
<td>35.2 ($17.4$)</td>
</tr>
</tbody>
</table>

*p < 0.05, **p < 0.01, ***p < 0.001
Analytical Strategy

Using an ITT approach, the aim was to determine the effect of EBM on failure rates in the open prison estate. A sequential logistic regression analysis was performed to determine the predictive ability of group membership (EBM vs. control). Given residency in open prison is time-limited as a function of sentence type/length, which varied across the sample, it was necessary to estimate and control for time ‘at risk’ in open conditions. This was necessary given the potential bias for instance, of comparing the likelihood of survival for prisoners serving longer compared to shorter sentences given the additional time ‘at risk’ of failure in open conditions. For indeterminate prisoners who failed in open conditions, this date was estimated based on their next scheduled parole hearing. Given actual time at risk is subject to the impact of failure/recall events, it was necessary to generate an ‘expected’ time at risk (i.e., expected release date minus arrival in open conditions date). Expected time at risk ranged from 48 to 2,214 days with a Mean expected stay of 495.67 days (SD = 263.53). Actual time at risk ranged from 20 to 2,214 days with a Mean actual stay of 364.72 days (SD = 299.46). At Block 1 therefore, the expected time-at-risk variable was entered into the analysis, followed by the group variable at Block 2. Area Under the receiver-operating characteristic Curve (AUC) analyses were also performed on the data to test the performance of the model, and Kaplan-Meier tests to compare the survival rates of the EBM and control group to determine whether EBM had any effect on longevity in open conditions.

ITT is an effective method for drawing conclusions about the attempt to intervene – exposing problems in referral procedures and programme retention but, arguably, has limitations in assessing the effects of the intervention actually received (cf. Hollin, 2008; Kovach, 2020). The intervention group is not only inclusive of those
who were discharged from EBM management per-protocol (i.e., completers) but also those who failed before starting (i.e., non-starters) or completing (i.e., non-completers). These groups potentially dilute any positive effect of EBM. As such, a treatment received (TR) approach was also adopted, repeating the above sequential logistic regression analysis, to understand whether completion of EBM per-protocol had any discernible impact on failure rates compared with a matched sub-group of control cases.

Results

Intention to Treat Analysis

Univariate Analysis

The majority (n = 211 [61.7%]) of the sample failed in open conditions. Except for four failures which could not be verified, 23 of 211 absconded (10.9%), five re-offended (2.4%), and five breached the terms of their temporary release licence (2.4%). The remaining and most significant proportion of the failures were security recalls (n = 174; 82.5%). Of the sample released into the community for at least one year (n = 272), 20 (7.4%) reoffended and 58 (21.3%) were recalled to custody.

The EBM group failed in open conditions more frequently (n = 126) than the control group (n = 85). The difference was statistically significant $\chi^2 (1, N = 342) = 20.80, p < .001$. However, the number of serious recidivistic events did not differ across the samples with 12 (7.1%) of the EBM group absconding (Control group: n = 11; 6.5%), three (1.8%) re-offending (Control group: n = 2; 1.2%) and two (1.2%) breaching the terms of their licence (Control group: n = 3; 1.8%). The biggest difference between the two groups was in the number of security recalls with 63.5% (n = 108) of the EBM group being recalled for security reasons compared to 37.9% of
the control group (n = 66). The actual mean time ‘at risk’ for the EBM group (282.47 days) was shorter, but not significantly, than for the control group (307.08 days). Of those released to the community for at least one year, there was no difference in re-offending rates between the EBM and control group (8.8% vs. 6.1%). Those in the EBM group were however, more likely to be recalled in their first one-year of release compared to the control group (29.6% vs. 14.3%). The difference in recall rate was statistically significant $\chi^2 (2, N = 272) = 11.16, p = .004$.

**Multivariate Analysis**

A sequential logistic regression analysis was performed to determine the predictive ability of group membership (EBM or control) on failure after controlling for the effects of time at risk. At Block 1, the expected time-at-risk variable was entered followed by the group membership variable at Block 2.

The constant-only model containing the intercept was significant $\chi^2 (1, N = 342) = 18.36, p < .001$. The time-at-risk variable, entered at Block 1, was also significant, $\chi^2 (1, N = 342) = 10.39, p = .001$. The model correctly classified 64.3% of cases but was more effective at correctly identifying failures (95.3%) compared to non-failures (14.5%). The model was not a good fit according to the Hosmer and Lemeshow test, $\chi^2 (8, N = 342) = 46.39, p < .001$. Group membership, entered at Block 2, also predicted failure $\chi^2 (1, N = 342) = 22.50, p < .001$. In comparison to the model at Block 1, in Block 2 there was a marginal increase in the number of cases being correctly classified overall (67.0%), with improved specificity at predicting non-failures (37.4%) albeit at the expense of identifying failures (85.3%). The model fit remained poor, $\chi^2 (8, N = 342) = 33.57, p < .001$. An AUC of .679 indicated moderate model predictive accuracy. Table 4.2 shows how the predictor variables contributed to the model. The
odds ratio (Exp [B]) indicates that assignment to the EBM group increased the odds of failure from a factor of two to a factor of three.

### Table 4.2

*Intention to Treat Analysis: Logistic Regression of Failure as a Function of Time-at-Risk and Group Membership (Intervention, Control)*

<table>
<thead>
<tr>
<th>Block 0</th>
<th>Variable</th>
<th>B</th>
<th>SE</th>
<th>Wald</th>
<th>Exp (B)</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Constant</td>
<td>0.48</td>
<td>0.11</td>
<td>18.36</td>
<td>1.61</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Block 1</th>
<th>Variable</th>
<th>B</th>
<th>SE</th>
<th>Wald</th>
<th>Exp (B)</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expected time at risk (days)</td>
<td>-0.00</td>
<td>0.00</td>
<td>10.38</td>
<td>1.00</td>
<td>[0.99-1.00]</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>1.21</td>
<td>0.25</td>
<td>22.63</td>
<td>0.00</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Block 2</th>
<th>Variable</th>
<th>B</th>
<th>SE</th>
<th>Wald</th>
<th>Exp (B)</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time at risk (days)</td>
<td>-0.02</td>
<td>0.01</td>
<td>12.61</td>
<td>1.00</td>
<td>[0.99-1.00]</td>
</tr>
<tr>
<td></td>
<td>Group membership (Int = 1, Cont = 0)</td>
<td>1.13</td>
<td>0.28</td>
<td>22.50</td>
<td>3.11</td>
<td>[1.95-4.97]</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>0.78</td>
<td>0.27</td>
<td>8.43</td>
<td>2.19</td>
<td></td>
</tr>
</tbody>
</table>

*Note. Classification Accuracy Block 0 = 61.7%, Block 1=64.3%, Block 2=67.0%*

A Kaplan-Meier test showed that assignment to the EBM group reduced the survival time in open conditions compared to the control group $\chi^2 (2) = 19.11 \, p < .001$. Assignment to the EBM group increased the hazard of failure by 112% (HR = 2.12; CI = 1.60, 2.80).

### Treatment Received Analysis

*Univariate Analysis*

Of the 171 offenders in the intervention group, 78 (45.6%) were discharged from EBM per-protocol (completers), 71 (41.5%) started but failed in open conditions during the course of EBM (non-completers), and 22 (12.9%) failed in open conditions before EBM commenced (non-starters). The descriptive statistics for the three
intervention groups alongside the control group are shown in Table 4.3. Kruskal-Wallis and chi-square analyses confirmed that there were no significant differences between the four groups on the matching variables: behavioural warnings $\chi^2 (3, N = 342) = 6.12, p = .106$; OVP score $\chi^2 (3, N = 342) = 4.03, p = .258$; or personality disorder diagnosis $\chi^2 (9, N = 342) = 9.29, p = .411$.

**Table 4.3**

*Descriptive Statistics by ‘Treatment Received’ Group*

<table>
<thead>
<tr>
<th>Variable</th>
<th>Completers (n = 78)</th>
<th>Non-completers (n = 71)</th>
<th>Non-starters (n = 22)</th>
<th>Control group (n = 171)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, M years (SD)</td>
<td>39.6 (11.6)</td>
<td>36.3 (11.5)</td>
<td>34.1 (8.4)</td>
<td>35.6 (10.7)</td>
</tr>
<tr>
<td>Previous convictions, M$_{number}$ (SD)</td>
<td>14.0 (11.6)</td>
<td>15.9 (11.2)</td>
<td>15.6 (14.9)</td>
<td>13.2 (10.7)</td>
</tr>
<tr>
<td>Index offence (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Burglary</td>
<td>7.8</td>
<td>9.9</td>
<td>4.5</td>
<td>9.8</td>
</tr>
<tr>
<td>Drug</td>
<td>0.0</td>
<td>1.4</td>
<td>4.5</td>
<td>2.4</td>
</tr>
<tr>
<td>Fraud</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
<td>0.0</td>
</tr>
<tr>
<td>Robbery</td>
<td>24.7</td>
<td>19.7</td>
<td>31.6</td>
<td>19.5</td>
</tr>
<tr>
<td>Sexual</td>
<td>26.0</td>
<td>23.9</td>
<td>4.5</td>
<td>20.1</td>
</tr>
<tr>
<td>Violence</td>
<td>32.5</td>
<td>36.6</td>
<td>54.5</td>
<td>41.5</td>
</tr>
<tr>
<td>Other</td>
<td>9.0</td>
<td>8.5</td>
<td>0.0</td>
<td>6.7</td>
</tr>
<tr>
<td>Sentence type (%)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Determinate</td>
<td>17.9</td>
<td>23.9</td>
<td>27.3</td>
<td>44.4</td>
</tr>
<tr>
<td>Indeterminate for Public Protection</td>
<td>43.6</td>
<td>50.7</td>
<td>45.4</td>
<td>35.7</td>
</tr>
<tr>
<td>Life</td>
<td>38.5</td>
<td>25.4</td>
<td>27.3</td>
<td>19.9</td>
</tr>
<tr>
<td>Behavioural warnings in 12 months prior to transfer to open conditions M$_{number}$ (SD)</td>
<td>3.6 (4.0)</td>
<td>4.4 (4.1)</td>
<td>4.8 (3.3)</td>
<td>3.6 (3.6)</td>
</tr>
<tr>
<td>Personality Disorder Diagnosis</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Not assessed</td>
<td>41.0</td>
<td>54.9</td>
<td>54.5</td>
<td>39.8</td>
</tr>
<tr>
<td>Negative diagnosis</td>
<td>18.0</td>
<td>7.0</td>
<td>9.1</td>
<td>17.0</td>
</tr>
<tr>
<td>Subthreshold traits</td>
<td>25.6</td>
<td>26.8</td>
<td>27.3</td>
<td>31.0</td>
</tr>
<tr>
<td>Positive diagnosis</td>
<td>15.4</td>
<td>11.3</td>
<td>9.1</td>
<td>12.3</td>
</tr>
<tr>
<td>OASys Violence Predictor (OVP) score M$_{number}$ (SD)</td>
<td>32.4 (15.7)</td>
<td>37.6 (15.8)</td>
<td>32.5 (12.4)</td>
<td>35.2 (17.4)</td>
</tr>
</tbody>
</table>
Thirty-six completers (46.2%) failed in open conditions. This compared to a failure rate of 85 (49.7%) in the entire control group \((n = 171)\) and a failure rate of 40 (51.3%) in the matched control \((n = 78)\). \(\chi^2 (1, N = 154) = 0.23, p = .629.\) The difference in failure rate between the completer group and the matched sample was not statistically significant and was equivalent across each of the serious recidivistic events with four (5.1%) of the EBM group absconding (Control group: \(n = 4; 5.1\%\)), one (1.3%) re-offending (Control group: \(n = 0; 0.0\%\)) and two (2.6%) breaching the terms of their licence (Control group: \(n = 3; 3.9\%\)). Of those released to the community, control group cases \((n = 147)\) were much less likely to be re-incarcerated for any reason \((n = 30; 20.4\%\)), compared to EBM completers \((n = 22/63; 34.9\%\)), non-completers \((n = 18/47; 38.3\%\)), and non-starters \((n = 8/15; 53.3\%\)). The finding was statistically significant \(\chi^2 (6, N = 272) = 14.44, p = .025.\) Whilst the community re-offending rates between completers and their matched controls \((n = 130)\) were equivalent (8.1% vs 8.8%), completers were more likely to be recalled (27.4% vs 13.2%) compared to the control group. This was statistically significant \(\chi^2 (2, N = 119) = 4.08, p = .044.\)

**Multivariate Analysis**

A sequential logistic regression analysis was performed to determine the predictive ability of group membership (completer or matched control) for failure, after controlling for time at risk. As previously, at Block 1 the expected time-at-risk variable was entered followed by the group membership variable at Block 2.

Table 4.4 shows the logistic regression model. The constant-only model containing the intercept was not significant \(\chi^2 (1, N = 156) = 0.10, p = .749.\) At Block 1, the model, upon entering the expected time-at-risk variable was non-significant, \(\chi^2 (1, N = 156) = 3.76, p = .053.\) The model correctly classified 61.5% of cases, 64.5% of failures and 58.8% of non-failures, but did not produce a good model fit based on the
Hosmer and Lemeshow test, $\chi^2 (8, \; N = 156) = 18.24$, $p = .020$. Group membership was added at Block 2 but did not contribute significantly to the model $\chi^2 (1, \; N = 154) = 0.06$, $p = .804$. There was no improvement in classification accuracy with 63.2% of failures and 60.0% of non-failures correctly identified. Overall, EBM completers were no more or less likely to fail compared to the matched control group.

**Table 4.4**

*Treatment Received Analysis: Logistic Regression of Failure as a Function of Time-at-Risk and Group Membership (Completer, Matched Control)*

<table>
<thead>
<tr>
<th>Block 0</th>
<th>Variable</th>
<th>B</th>
<th>SE</th>
<th>Wald</th>
<th>Exp (B)</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Constant</td>
<td>-0.51</td>
<td>0.16</td>
<td>0.10</td>
<td>0.95</td>
<td>[0.86-1.00]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Block 1</th>
<th>Variable</th>
<th>B</th>
<th>SE</th>
<th>Wald</th>
<th>Exp (B)</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Expected time at risk (days)</td>
<td>-0.00</td>
<td>0.00</td>
<td>3.76</td>
<td>1.00</td>
<td>[0.99-1.00]</td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>0.60</td>
<td>0.37</td>
<td>2.66</td>
<td>1.83</td>
<td>[0.99-1.76]</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Block 2</th>
<th>Variable</th>
<th>B</th>
<th>SE</th>
<th>Wald</th>
<th>Exp (B)</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time at risk (days)</td>
<td>-0.01</td>
<td>0.01</td>
<td>3.47</td>
<td>1.00</td>
<td>[0.99-1.00]</td>
</tr>
<tr>
<td></td>
<td>Group membership (Int = 1,</td>
<td>-0.08</td>
<td>0.33</td>
<td>0.06</td>
<td>0.92</td>
<td>[0.48-1.76]</td>
</tr>
<tr>
<td></td>
<td>Cont = 0)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>0.63</td>
<td>0.38</td>
<td>2.68</td>
<td>1.88</td>
<td>[0.99-1.76]</td>
</tr>
</tbody>
</table>

*Note.* Classification Accuracy Block 0 = 51.3%, Block 1=61.5%, Block 2=61.5%

**Discussion**

This study aimed to determine whether Enhanced Behaviour Monitoring (EBM) is effective at reducing failures in open prisons in England and Wales. Behavioural monitoring can unlock risk-related information, inaccessible to other risk assessment methodologies, and act as a foundation from which to intervene at critical moments in an offender’s journey away from crime. There is precedent in forensic samples for
successfully intervening on the basis of behavioural monitoring protocols (Tolisano et al., 2017; Ward & Bosek, 2002). EBM contains a feedback loop to encourage self-management of risk and on that basis, it was hypothesised that EBM would impact positively on ‘failure’ rates, despite the additional monitoring.

The hypothesis was not supported by the data. Using an Intention To Treat (ITT) approach with a matched control group, the results showed, that whilst there were no differences in serious failure outcomes between the intervention and control groups, those allocated to EBM were returned to closed conditions sooner, and at greater frequency; indicating perhaps that EBM was primarily being used as a surveillance tool, to detect rule violations (Hyatt & Barnes, 2017; Petersilia & Turner, 1993). Yet those completing EBM per-protocol in the Treatment Received (TR) analyses were slightly more likely to survive in open conditions compared to their matched control group, with no increase in serious failure outcomes, albeit the finding did not reach significance. In sum, in this paper, I was unable to demonstrate the efficacy of behavioural monitoring – namely EBM – as a tool for reducing failures in open conditions by rehabilitative means.

However, equally, I am unable to unequivocally dismiss the potential of EBM as an intervention; it is important first, to acknowledge and digest the methodological limitations underpinning these findings. Indeed, despite best efforts to match members of the control group to the EBM group, a common criticism of Propensity Score Matching (PSM) analysis is that it may omit, principally due to nonrecognition, the effect of several unmeasured but clinically relevant factors that can affect the outcome (Reiffel, 2020). Our study was limited to matching on the basis of three variables only (i.e., behavioural warnings in custody, OVP score, personality difficulties), as identified in Chapter 3. These data were collected from administrative
databases, but propensity scores derived from largely administrative data do not necessarily balance unmeasured clinical confounders (Austin et al., 2005). Indeed, a relatively small proportion of the control group – just one-third – could be matched to the intervention group indicating that the two groups were already distinct and classifiable at the outset. It is possible therefore that the matching variables may have been acting as a proxy for a particular clinical profile represented more frequently in the EBM group and which, based on administrative data, was matched superficially in the control group. Indeed, the decision to allocate to EBM is decided by psychological professionals trained in risk assessment. It is likely that these professional decisions were based in an aggregation of risk-relevant factors, meaning the potential available control group was comprised of a greater proportion of men who were likely to be successful in open conditions. In this context, the EBM cohort performed surprisingly well and the per-protocol results may be considered to represent a conservative estimate (possible under-estimate) of the effect of EBM on failure rates.

This paper does, however, stop short of proposing a positive effect of EBM – in its current form – on failure rates. Indeed, whilst there are limitations in directly comparing the outcomes of the intervention group against the outcomes for the control group, there existed patterns in the descriptive data indicating a ‘blunting’ of any intended rehabilitative impact of EBM. First, the ratio of security recalls to community re-offending was approximately 7:1 across both the EBM group \((n = 108/15)\) and the control group \((n = 66/10)\). That is, for every community re-offence by an individual in each group, an equivalent of seven individuals were returned to closed conditions. Ostensibly therefore, the approach to non-compliance remained consistent regardless of EBM allocation; additional time/space for behavioural improvement was not afforded to those allocated to EBM. Second, whilst the sample
was purposively selected and included those at highest risk of open prison failure, the one-year community re-offending rates were similarly low across both groups (intervention 8.8%; control 6.1%), certainly relative to the security recall rate. As argued in Chapter 3, and as per the tenet of this paper, it should be possible to reduce in-prison failure rates without adversely impacting the community recidivism rate.

The intensive supervision literature contains key lessons for EBM. ‘Surveillance only’ supervision programmes (i.e., those without a rehabilitative component) serve only to increase the rate of reincarceration due to technical violation but have null effects on recidivism (Drake, 2018; Hyatt & Barnes, 2017; Petersilia & Turner, 1993). Only those supervisory approaches which incorporate a therapeutic component or where supervisors act as ‘agents of change’, positively impact on recidivism outcomes (Bonta et al., 2011; Drake, 2018; Petersilia & Turner, 1990; Taxman, 2008). A process evaluation is a necessary next step to examine the implementation of EBM to seek ways to reinforce the rehabilitative component. Likewise, the organisational context or philosophy of the institutions in which EBM has been implemented may be important. Clear and Latessa (1993) found that the personal role preferences of probation officers (i.e., law enforcement vs. social worker) were mediated by the philosophy of the institution. Results from Chapter 3 demonstrated that open prisons in England take a conservative approach to non-compliance – a function of the socio-political context in which these prisons operate – which might be permeating any rehabilitative potential within EBM. Muir-Cochrane and colleagues (2012) refer to a phenomenon of ‘anxious vigilance’ in which staff, fearful of the consequences of serious failure outcomes such as absconding, are hypervigilant to the threat, at the expense of patient care. Conversely, good relational security and a supportive culture may be more promising as risk management strategies (Emirali et al., 2020; Mezey et
al., 2015) certainly in comparison to regimes with a law enforcement orientation (Alexander, 2006).

**Practical Implications**

Whilst it has not been possible to demonstrate the effectiveness of Enhanced Behaviour Monitoring (EBM) to stabilise behaviour, and so advocate for the use of behavioural monitoring protocols as an intervention in open prisons internationally, several practical points should be noted. First, despite purposively sampling those residents deemed by practitioner psychologists to have a raised risk profile for failure (i.e., the intervention group), 8.2% absconded or re-offended in custody and 8.8% re-offended within one year of being placed in the community. Manifestly therefore, the recall rate of 63.2% was grossly disproportionate to the risk. Given open prisons’ purpose is to prepare prisoners for release thereby reducing community recidivism, on the balance of risk, open prisons should defer recall decisions in favour of allowing a greater accumulation of behavioural data. McDougall and colleagues (2013) have previously shown that the frequency of concerning behaviours in custody and the frequency in the community were significantly correlated and that, based on custodial frequency, community recidivism could be predicted with 92% accuracy. Therefore, behavioural schemes such as EBM could be used effectively to inform community release management rather than being a tool for managing risk *while in* open prisons. Chapter 3 argues that systems-level policy implementation should be the primary means of ensuring effective risk management in open prisons. Basing re-categorisation decisions in comprehensive risk assessment, softening transitions to and within open prisons, and building secure accommodation provision into open sites is the measured approach to risk management; certainly preferable to dropping unsuitable candidates into an unstructured environment and relying on open prisons
‘spotting’ or ‘catching’ the residual risk. Indeed, there is no precedence for using
behavioural schemes purely as a surveillance tool without a rehabilitative component.
Drake (2018), using a Monte Carlo simulation analysis of the likely risk and uncertainty
of investing in various Intensive Supervision Programmes (ISPs) based on their meta-
analytic effect size for reducing recidivism, showed that the benefits of investing in
ISPs with a rehabilitative component far outweighed the costs. ‘Surveillance only’
programmes had a null effect on recidivism at best. Arguably therefore, open prisons
should use behavioural monitoring protocols, not as a tool for defending against risk
exposure, but to support and underpin risk formulations to support effective
management on release.

Conclusions

The results of the current study examining the effectiveness of a behavioural
monitoring scheme (EBM) for reducing failures in open conditions in England and
Wales were inconclusive. Despite our best efforts to match the EBM group to a
suitable control, there are reasons to believe that the two groups differed from one
another at the outset and the, largely administrative-level, variables identified in the
literature as relevant to failure in open conditions were insufficient to balance
unmeasured clinical confounds. Nonetheless, an examination of the descriptive data
indicated that prison managers adopted a similar approach to behavioural aberrations
across both groups, indicating, at best, that EBM was having a null impact on
behavioural stabilisation. Reductions in recidivism are possible with behavioural
monitoring interventions (Tolisano et al., 2017; Ward & Bosek, 2002) and intensive
supervision programmes with a rehabilitative component (e.g., Bonta et al., 2011). A
process evaluation is necessary to understand the barriers to realising the
rehabilitative potential within EBM. Consideration should also be given to re-
purposing EBM as a tool for formulating and steering risk management on release to the community.
Chapter 5: General Discussion
Chapter 5: General Discussion

The open prison estate plays an important and unique role in the rehabilitation and resettlement of offenders. There is evidence to suggest that spending more time in open prison, in comparison to a closed prison, impacts on recidivism rates to a statistically significant and economically meaningful degree (Mastrobuoni & Terlizzese, 2022). This finding is likely underpinned by a myriad of mechanisms including both the practical and psychological benefits associated with gradual exposure to the community (Andvig et al., 2021; Baumer et al., 2009; Hillier & Mews, 2018; Ministry of Justice, 2015, 2019b). Yet, the concept of an open prison is controversial.

Given the absence of perimeter security, minimal supervision arrangements, limited restrictions on activity/movement, and ready access to the public, there is an increased hazard that harmful behaviours will spill out into the community; behaviours which might otherwise be contained by the walls of a closed prison (cf. Price, 1971). Serious recidivistic events, such as abscond or re-offending, attract public outrage and political scrutiny which can have wide-ranging repercussions for the affected institution (cf. Dawar & Davis, 2014; Reichlin & Bloom, 1993). This often includes policy change; change which might be disproportionate to the risk (Moore, 2000) and even result in other unintended negative consequences which undermine rehabilitative efforts (cf. Bowers et al., 2006). Recent legislative changes in England and Wales, giving the Justice Secretary power to veto recommendations to move prisoners to open, is a potential case in point (cf. Hymas, 2022).

As already outlined, following a review into a series of further offences by prisoners resident in open conditions in England and Wales (HM Inspectorate of Prisons, 2014), Her Majesty's Prison and Probation Service (HMPPS) implemented an
Enhanced Behaviour Monitoring (EBM) framework (NOMS, 2015a). EBM was developed and implemented instantly, within four months of the HM Inspectorate’s review. The purpose was to provide assurance that ongoing risks (i.e., abscond, harm, reoffending) posed by prisoners in open prisons were appropriately identified and managed via a comprehensive Case File Review (CFR) and behavioural monitoring protocol for those deemed at heightened risk of failure. However, the EBM Prison Service Instruction (NOMS, 2015a) contained notable omissions, namely a clear theoretical basis, definitive guidance on the targeting of EBM, and the provision for an evaluation strategy. As such, the overall aim of the current research was to evaluate the impact of EBM on reducing failure outcomes such as abscond, re-offending, and temporary release failure (TRF).

To produce a controlled evaluation, it was necessary to develop a comprehensive understanding of ‘who fails’ in open conditions to draw conclusions about the effectiveness of EBM, as a preventative mechanism against such outcomes. However, open prison failure is vastly understudied, and the extant literature is weakened by methodological shortcomings (see Chapter 1). As such, Study 1 comprised a comprehensive meta-analysis to isolate those factors which consistently predict community failure in a subset of adult offenders in the immediate years following release from custody. This mirrored, as closely as possible, the timeline and risk exposure of those transferring to open prison. In Study 2, failure events in open conditions such as abscond, re-offending, and TRF were regressed onto these factors, in addition to a set of factors extrapolated from surveying a group of ‘open prison experts’ (practitioner psychologists working in open prisons) and the literature into absconding from forensic psychiatric facilities, primarily. In Study 3, those predictors which significantly contributed to the prediction model were used to match those
individuals subject to EBM intervention with a control group, to evaluate the impact of EBM on abscond, re-offending, and TRF.

In Study 1, using meta-analytic techniques, 17 risk factors had associations – across both bivariate and multivariate analyses – with increased or decreased risk of recidivism in adult male offenders in the immediate year following release from custody. These factors were broadly consistent with the ‘central eight’ risk factors described by Bonta and Andrews (2017) in their General Personality and Cognitive Social Learning (GPCSL) theory and particularly those domains indicative of antisocial potential (‘big four’): History of Criminal Behaviour; Antisocial Personality Pattern; Antisocial Cognitions; Antisocial Companions (Andrews et al., 2006). However, whilst the recidivism prediction literature is a well-established field of research, integrated via meta-analyses (Bonta et al., 2014; Gendreau et al. 1996; Lipsey & Derzon, 1998), it is not without its limitations. Indeed, from a pool of over 600 individual effect sizes taken from the highest quality studies, Study 1 found only 21 risk predictors were studied four or more times and could be used in the data analysis. These factors were primarily static in nature and there was substantial heterogeneity in the results which could not be explained by a set of moderator variables considered important in the literature (Singh et al., 2014). Indeed, the absence of dynamic risk factors is potentially problematic given the likely importance of both stable and acute dynamic factors underpinning failure events such as abscond from open prisons (i.e., Berman-Roberts, 2015; Chant, 2015; Papworth, 2015; Picksley, 2016; Roberts, 2016). Where dynamic risk factors had been analysed, these were typically measured once in those studies reporting relevant effect sizes, thereby removing their ‘dynamic’ component (cf. Harris & Rice, 2015).
Thus, whilst Study 1 provided a compelling ‘basis’ from which to predict failure outcomes (abscond, re-offending, TRF) in open conditions, it was insufficient alone; notwithstanding the apparent qualitative differences between open prison residency and release on licence. As such, it was necessary to supplement these risk factors. Additional variables with potential predictive utility were identified by surveying a group of expert practitioner psychologists working in open prisons, and through consultation with the literature into abscond, albeit primarily concentrated in forensic psychiatric samples. Following this method, a total of 26 risk factors were identified as potentially relevant. In Study 2, a sample of 316 prisoners were followed in open conditions until release or a failure event. However, serious recidivistic events such as abscond were rare and re-offending occurred exceptionally; consistent with previous research (Banks et al., 1975; Dissel, 2008; Hillier & Mews, 2018; Leitch, 1951; Porritt, 1982). Indeed, serious recidivistic events were so rare in Study 2 that it was not possible to regress these outcomes onto the independent variables. It is likely that some of these events were diverted by recalling prisoners back to closed conditions before risk manifested. Study 2 uncovered a culture of risk aversion in which those deemed to be displaying behaviour indicative of risk escalation were recalled to closed conditions for security reasons, at high frequency. This group \( n = 83/316; 26.3\% \) comprised the majority of all failures \( n = 100/316; 31.6\% \), yet those released from custody \( n = 72/83 \) re-offended at low rates \( n = 7/72; 9.7\% \). To achieve ‘sensitivity’ (i.e., identifying true positives) in reducing serious adverse failure events, open prisons were compromising on the ‘specificity’ (i.e., overlooking the false positives) of their risk judgments, a function perhaps of the socio-political context in which they exist. Muir-Cochrane and colleagues (2012) refer to a phenomenon in forensic psychiatric hospitals which they coined ‘anxious vigilance’ whereby staff, fearful of the
consequence of serious failure outcomes such as absconding, become hypervigilant to the threat, at the expense of patient care.

Developing a better understanding of the security recall group became a priority in Study 2; a prevailing perception of risk escalation existing around this group, not otherwise evinced by their subsequent community re-offending rates. A regression analysis identified five variables predicting security recall although the overall model was more effective at identifying true negatives not recalled (93.8%) than true positives recalled (62.7%). In order of effect size the variables were:

- Substance misuse in the six months to outcome (OR = 17.46, 95%CI: 5.99, 50.89);
- Adjudications in six months to outcome (OR = 10.63, 95%CI: 4.21, 26.85);
- Diagnosis of personality disorder (OR = 5.20, 95%CI = 2.01, 13.46);
- Behavioural warnings in the 12 months to transfer to open conditions (OR = 1.42, 95%CI = 1.21, 1.67);
- OASys Violence Predictor (OVP) score (OR = 1.05, 95%CI = 1.03, 1.08).

Arguably, those variables with the largest effect sizes were markers for adverse behavioural changes being detected by open prison staff. Risk aversion aside, this was an encouraging pattern given behavioural monitoring has been shown to have utility in predicting community re-offending (McDougall et al., 2013). Yet, notably, behavioural warnings in the six months prior to outcome did not predict failure, perhaps indicating that security recalls were being directed on little more than single observable events as opposed to an accumulation of misdemeanours; a more reliable indicator, arguably, of antisocial persistence (Buss & Craik, 1983; Pearson & McDougall, 2017). Likewise, experiencing adverse events akin to those ‘push’ and ‘pull’ factors for abscond, as observed in previous studies (i.e., Berman-Roberts, 2015; Chant, 2015; Papworth, 2015; Picksley, 2016; Roberts, 2016) did not predict failure. However, it is likely that those variables were insufficiently nuanced to understand the interaction between
the individual and the situation (cf. Mischel & Shoda, 1995), a matter returned to later.

The evaluation of EBM as an intervention – to divert potentially vulnerable prisoners away from serious recidivistic events – was considered in Study 3. A sample of 171 offenders subject to EBM was matched to a control group, based on those variables predictive of security recall but unaffected by the EBM intervention itself. Study 3 found EBM to have null effect on serious recidivistic outcomes overall and the findings were not able to support previous research, by demonstrating the utility of behavioural monitoring as an intervention (Simpson et al., 2015; Tolisano et al., 2017; Ward & Bosek, 2002). It is important to note, however, that just one-third of the potential pool from which the control group was selected could be matched, perhaps indicating that the two groups were already distinct and classifiable at the outset. Nonetheless, analysis of the respective proportion of security recalls to community re-offences (7:1) indicated that non-compliance was being treated similarly across both the intervention and control groups. That is, any intended rehabilitative component within EBM is being ‘blunted’. The intensive supervision literature provides a cautionary tale however; ‘surveillance only’ supervisory approaches increase the rate of reincarceration due to increased technical failure whilst having null effects on recidivism rates (Drake, 2018; Hyatt & Barnes, 2017; Petersilia & Turner, 1993). Via EBM at least, the opportunity to formulate, rehabilitate, stabilise, or support prisoners is being missed.

Limitations

Before illustrating both the theoretical and practical implications of this thesis, it is necessary first to absorb the limitations. Indeed, the primary limitation of this thesis, arguably, concerns the method for determining any potential effect of
Enhanced Behaviour Monitoring (EBM) on failure outcomes. A Randomised Control Trial (RCT) was not feasible given the potential implications of withholding EBM (i.e., failing to mitigate risk to the public). It was necessary therefore to adopt an observational experimental design, matching those assigned to the EBM group, to a control group, as closely as possible. Study 3 adopted Propensity Score Matching (PSM) with nearest neighbour matching and specified an accepted maximal caliper distance between matches (Austin, 2011) to minimise sampling bias. Despite best efforts, however, there is credible evidence that there remained systematic differences in key baseline characteristics between the EBM group and the matched control group. That is, a relatively small proportion of the entire available control group – just one-third – could be matched to the EBM group indicating that the two groups were already distinct and classifiable at the outset. There are several possible explanations for this. First, it seems plausible that the two groups were distinct since the decision to allocate to EBM is decided by psychological professionals trained in risk assessment. It is likely that these decisions were based in an aggregation of risk-relevant factors, meaning the potential available control group was comprised of a greater proportion of men who were likely to be successful in open conditions. Second, and as discussed earlier, the extant research into failure outcomes in open prisons is limited (see Chapter 1). As such, the characteristic differences between those who fail in open conditions compared to those who succeed, has not been reliably established. Whilst Study 2 isolated – from a potential pool of 26 – three usable variables not confounded by the potential impact of EBM (i.e., prior behavioural warnings, OVP score, personality difficulties), it is plausible that other, as yet identified risk factors, have greater utility in differentiating successes and failures; a matter returned to later. Moreover, one could argue that these variables are, to
some extent, administrative, or at least, insufficiently nuanced to detect potentially important clinical confounders (Austin et al., 2005). It is possible, therefore, that the matching variables may have been acting as a proxy for a particular clinical profile represented more frequently in the EBM group and which, based on administrative data, was matched superficially in the control group. On that basis, the utility of EBM as an intervention is not to be dismissed prematurely without a process evaluation.

**Theoretical Implications**

This thesis raises several theoretical implications for the risk prediction field. The field of correctional and forensic practice is predominantly informed by Bonta and Andrews’ (2010) Psychology of Criminal Conduct (PCC) and specifically their General Personality and Cognitive Social Learning (GPCSL) theory (Bonta & Andrews, 2017). They propose a ‘central eight’ risk factors for offending – criminogenic needs – which, in accumulation and interaction with one another, increase the likelihood of criminal behaviour. These ‘central eight’ factors consist of a combination risk factors which correlate with recidivism, both static or relatively fixed aspects, and dynamic which are potentially changeable and clinically meaningful. The GPSCL theory is supported and underpinned by hundreds of risk prediction studies, integrated via meta-analysis (Bonta et al., 2014; Gendreau et al., 1996; Lipsey & Derzon, 1998). It was plausible therefore to conceive the possibility of building of a reliable model to predict the various forms of recidivism observed by prisoners in open conditions. However, as outlined above, that pursuit was beset by various challenges.

First – and unrelated to the GPCSL theory – factors such as the paucity of literature into predictors of open prison failure, sample selection bias, the conflation of abscond and escapes (cf. Mews, 2014), small sample sizes (cf. Emirali et al., 2020), the low base rates of abscond/re-offending (cf. Chapter 3; Mews, 2014), and the
relatively higher rates of recall masking failure events (cf. Chapter 3; Ostermann et al., 2020), all limit the capacity for accurate prediction. Manifestly, further research, with larger sample sizes is needed to identify psychologically meaningful risk factors for abscond and other open prison failures, and for these risk factors to be subject to robust empirical testing to determine their predictive accuracy.

Yet, it is possible that the approach to identifying factors for testing in Study 2 was limited by the fundamental building blocks of the GPCSL theory in their current form. Some academics have identified a ‘plateauing’ in risk assessment accuracy (Coid et al., 2011; Wolf et al., 2018) and inconsistencies in the relationship between change in dynamic risk factors and recidivism (Klepfisz et al., 2016; Serin et al., 2013). These ‘ceiling effects’ have been linked to problems in the conceptual distinction between static and dynamic risk factors – and how these factors are measured (Harris & Rice, 2015; Heffernan et al., 2019a, 2019b). Beech and Ward (2004) argue against the notion that static and dynamic risk are separate entities and instead propose that static factors act as markers for the past operation of dynamic risk factors and reflect underlying propensities for offending rather than the cause of offending. The superior predictive capacity of static over dynamic risk factors (cf. Casey, 2016; Caudy et al., 2013; Coid et al., 2009; Morgan et al., 2013) may simply typify the fact that static factors are more easily and reliably measured (cf. Chapter 2; Lehmann et al., 2016). Heffernan and colleagues (2019b) contend that dynamic factors are effectively ‘hybrid’ concepts, consisting of a variety of contextual (e.g., gang membership), behavioural (e.g., use of weapons) and psychological state aspects (e.g., violent ideation) which frequently overlap. Indeed, practitioners report difficulties in defining various dynamic risk factors and moreover, signs of manifestation and amelioration (Sweller et al., 2016). Heffernan and colleagues (2019a, 2019b) also argue that the
causal link to recidivism has not yet been established and dynamic risk factors, in their current form, should be thought of as ‘symptom-like features’ of individuals and their environments.

The success of the GPSCL theory, has arguably, albeit unintentionally, stifled the search for alternative targets of explanation which have a causal link between the risk factor and recidivism; a criticism which can perhaps be levelled at the approach taken to Study 1 and the building blocks of this thesis. Yet, identifying targets of explanation and demonstrating a causal link is not only likely to be arduous, but might also represent a blind alley. Indeed, there is a strong argument to move away from explaining risk – both that of recidivism or abscond risk – nomothetically, and towards undertaking idiosyncratic or individualised assessments of risk and monitoring behaviour longitudinally (McDougall et al., 2013; Pearson & McDougall, 2017). This is not the same as moving to unstructured clinical judgement which has been long established as no more effective than chance at predicting recidivism (Grove & Meehl, 1996; Meehl, 1954) but rather understanding the function of the behaviour for the individual (cf. Ward & Carter, 2019) and observing how that behaviour manifests or changes over time. McDougall and colleagues (2013) have shown that such techniques can exceed 90% risk prediction accuracy.

Indeed, a behaviour monitoring scheme enables improved understanding of the function of behaviour, in the wider environmental context. For instance, several ‘push’ and ‘pull’ factors for abscond are beginning to emerge in the literature (Berman-Roberts, 2015; Chant, 2015; Papworth, 2015; Picksley, 2016; Roberts, 2016) albeit these factors have, thus far, largely been overlooked by larger-scale studies in favour of individual-level factors (e.g., Mews, 2014). Whilst Study 2 did account for adverse events akin to these ‘push’ and ‘pull’ factors, their coding was likely
insufficiently nuanced to understand the interaction between the person and the situation. Indeed, Mischel and Shoda (1995) propose that behaviour is person-situation specific such that situational cues trigger mental representations of beliefs, memories, images etc., and subsequently activate associated behavioural strategies. For instance, the tolerance level for absconding, will likely differ between individuals faced with the same situational triggers, if indeed the behavioural repertoire for absconding exists at all for some of those individuals. As such, this thesis advocates for further research into the role of dynamic (Dunbar, 1985) or relational security in preventing open prison failures; this notion that knowing the individual and how changes to their outside world (e.g., outward connections), their inside world (e.g., perception of their physical environment; personal world), and/or the dynamics of that inside world (e.g., relationships with other prisoners; prisoner mix) represents the best method for understanding and identifying risk manifestation.

Relatedly, this thesis highlights the importance of conducting longitudinal monitoring of behaviour to enable more accurate assessments of risk. It is noteworthy that engaging in substance misuse whilst resident in open conditions, and behaviours meeting the threshold for adjudication, were most strongly associated with prison failure. Conversely, factors such as number of behavioural warnings in open prison did not predict prison failure despite previous research highlighting the importance to recidivism prediction of behavioural ‘aggregation’ (Hanson et al., 2007; McDougall et al., 2013). As such, it is plausible that at least some individuals were being returned to closed conditions following single-episode behaviours which might also explain the weak relationship between security recall and community recidivism in chapter 3. Indeed, Buss and Craik (1983) suggest that act frequency – the number of behaviours observed – is a much better measure of personality and therein, the
extent to which an individual has made enduring changes which are likely to impact on recidivism (Clark et al., 1993). Moreover, an aggregation of ‘low-level’ behaviour such as bullying or horseplay might be as important to risk as those behaviours with clearer empirical associations with recidivism (McDougall et al., 2013).

In sum, this thesis argues for a move away from nomothetic explanations of risk, towards idiosyncratic or individualised assessments of risk. Indeed, it was not possible in Study 2 to reliably predict failures in open prisons based on ‘cookie cutter’ risk factors for recidivism. Encouragingly, prison staff were identifying markers for adverse behavioural changes – the basis for making individualised assessments of risk. However, the risk tolerances of prison managers were not well calibrated, with an inclination for risk aversion, perhaps indicating that recall decisions were being made based on decontextualised single-episode behaviours rather than behavioural aggregation (Hanson et al., 2007; McDougall et al., 2013). Longitudinal behavioural formulation and monitoring – where the function of the behaviour can be understood and contextualised – favouring behavioural aggregation as a marker for ongoing risk manifestation or amelioration, bypasses many of the conceptual (Heffernan et al., 2019a; 2019b; Ward & Beech, 2004) and practical issues (Sweller et al., 2016) of assessing risk nomothetically, and has established utility as an effective risk prediction tool (McDougall et al., 2013).

Practical Implications

As discussed above, given the low base rates, predicting serious recidivistic events in open prison conditions at the individual-level with any precision, is likely futile. There has been a steady decline in serious recidivistic events, such as abscond, by those residing in open conditions in England and Wales, since a peak of 1,301 such events in 2003-2004 (Justice Data Lab, 2022). Whilst it is likely that this has been
achieved through multifarious factors, including the introduction of evidence-informed risk management policies (cf. NOMS, 2015b), it is evident from Study 2 that these effects are at least partially achieved by prison managers compromising on the specificity of their risk judgments and acting cautiously or defensively when exposed to risk information. Resultingly, a significant proportion of men embarking on a path of desistance, as evidenced by their one-year community re-offending rates in Study 2, are being recalled to closed prison conditions. The cost of this system can be counted economically with some certainty, yet the psychological cost is currently untold. The emphasis currently rests too greatly on open prisons ‘catching’ the supposed residual risk and in all likelihood, basing their decisions on information which is likely incomplete (cf. Mann & Atkinson, 2012) and, as indicated by Study 3, decontextualised (i.e., single episode behaviours).

Public safety assurance is unlikely to be achieved by changing one system or process but rather by multi-level systemic changes at the junctures in which the opportunity to influence risk, present. The first juncture is in the selection of men for open conditions. Currently, open prisons have limited influence over the re-categorisation of prisoners; the criteria are applied, depending on the parameters of the sentence, by prison managers in the closed estate or by the Public Protection Casework Section following a recommendation by the Parole Board (Ministry of Justice, 2020a). Clearly, as per Leitch (1951, p.26), it is necessary to take ‘some risks’ to ‘pick out the cases of doubtful prognosis for whom there is nevertheless a chance of social reclamation, and then to swing the balance in favour of social adaptation’. Yet it would seem imprudent to discount the experience and expertise of professionals from the open prison estate to exclude obviously inappropriate candidates for open prison, to mitigate risk exposure. Provision of a multi-disciplinary
board reflective of the various experts and stakeholders to review cases, and establish the risk, needs, and parameters under which the individual needs managing in that context, might be one such system worthy of further consideration.

Second, and as evinced in Andvig and colleagues (2021), prisoners moving to open conditions are exposed to several emotionally demanding ‘transitions’, the most obvious being the transition from a closed to an open prison. Yet it is likely that multiple other events or transitions exist in a prisoner’s journey through open conditions which are overlooked and provide context to an individual succumbing to those ‘push’ and ‘pull’ factors associated with abscond (cf. Berman-Roberts, 2015; Chant, 2015; Papworth, 2015; Picksley, 2016; Roberts, 2016). The transition from a period of temporary leave with loved ones back to prison life – described by one prisoner as ‘the worst punishment’ (Andvig et al., 2021) – is a case in point. It is during these periods of a prisoner’s journey that additional support is required and where relational or dynamic security is likely to be crucial to the identification of potentially relevant changes in individual circumstances. In 2016, HMPPS introduced the Offender Management in Custody (OMiC) model to support and manage prisoners through their sentence. This model includes a keyworker role; the role of the keyworker being to develop constructive, motivational relationships with prisoners to support them to make appropriate choices, instil hope, and encourage personal development. However, that element was dropped from the open estate model (HMPPS, 2021), it could be argued, misguidedly; the inference being that those residing in the open estate had already achieved the goals of the keyworker model. Re-evaluation of this is necessary; the keyworker model presents an opportunity for emphasising the importance of, and ensuring appropriate resourcing for, relational security.
Indeed, HMPPS already has a mechanism which has potential for identifying and intervening following the observation of risk-related behavioural changes – EBM. However, Study 3 concludes that any rehabilitative component within EBM is being blunted and, given the risk intolerance of prison managers within open conditions, is resulting in the recall of high numbers of men who do not go on to re-offend in the community. Authoritarian approaches to risk management have been found to be disruptive to the social equilibrium of the environment and associated with higher rates of aggression and absconding in forensic psychiatric facilities (Alexander, 2006; Urheim et al., 2011). It is already well-established that ‘surveillance only’ supervision programmes in the community have null effects on recidivism rates but result in substantial increases to the rates of technical violation (Drake, 2018; Hyatt & Barnes, 2017; Petersilia & Turner, 1993). Conversely, supervisory approaches which incorporate a therapeutic component and/or where supervisors act as ‘agents of change’ can positively impact on recidivism outcomes (Bonta et al., 2011; Drake, 2018; Petersilia & Turner, 1990; Taxman, 2008). A process evaluation of EBM is a necessary next step. It is only possible to reinforce or develop the rehabilitative component of EBM by evaluating its implementation and the context in which it operates.

The latter – the context – is important and as suggested by Study 1, is often overlooked in the risk prediction/prevention literature. This is exemplified by Clear and Latessa (1993) who demonstrated that the institutional policy had a mediating effect on the personal role preferences of probation officers (i.e., law enforcement vs. social worker). Indeed, there is emerging research to indicate that the social climate of an institution is an important factor in improving community outcomes for prisoners (Auty & Liebling, 2020) and that good relational security and a supportive culture may be more promising as risk management strategies (Emirali et al., 2020;
Mezey et al., 2015) than environments which are rule-enforcement oriented (Alexander, 2006). ‘Orderliness’ in prisons is likely best achieved by cultivating legitimate authority; only in a moral or legitimate social context is it possible for prisoners to create the space to develop personally and navigate away from criminality (Auty & Liebling, 2020). Fostering these cultures in open prisons should undoubtedly be a priority for HMPPS.

The socio-political climate in which open prisons operate is undoubtedly a limiting factor in their effectiveness. Release failures have damaging repercussions for the legitimacy of an institution (cf. Dawar & Davis, 2014; HM Inspectorate of Prisons, 2014; Reichlin & Bloom, 1993), and sustained political pressure can result in policy change which is disproportionate to the nature and outcome of the incident, adversely impacting rehabilitation delivery in some cases (Moore 2000). Indeed, recent changes to the open prisons tests applied by the Parole Board in England and Wales has adversely impacted the numbers of prisoners – particularly those serving long-term sentences – from accessing open prisons (cf. Hymas, 2022). This, despite evidence supporting their positive impact on recidivism rates (Mastrobuoni & Terlizzese, 2022) and the comparatively low incidence of serious recidivistic outcomes (Banks et al., 1975; Chapter 3; Dissel, 2008; Hillier & Mews, 2018; Leitch, 1951; Porritt, 1982). This cohort of prisoners will, principally, be released directly to the community in the future, but will miss out on the benefits of graduated release to the community (Ministry of Justice, 2015); the policy is likely to have criminogenic effects. The purpose of open prisons is to test and prepare prisoners for community release. Logically, their use should be extended rather than restricted, with recall decisions deferred to allow a greater accumulation of behavioural data. McDougall and colleagues (2013) have previously shown that the frequency of concerning behaviours
in custody and the community were significantly correlated and that, based on that frequency, community recidivism could be predicted with 92% accuracy. Therefore, behavioural schemes such as EBM could be used effectively to inform community release management rather than being a tool for managing risk while in open prisons. That is, using EBM to defend against risk exposure through the recall of prisoners is ineffectual, as evidenced in Study 3. It would be better applied as a mechanism for building a comprehensive risk formulation to inform effective risk management in the community and risk-relevant conversations between offender and offender manager.

In sum, this thesis finds the risk tolerance of open prisons too heavily weighted towards risk aversion as a mitigation to risk manifestation. Whilst ‘zero tolerance’ approaches to risk management are intuitive, the evidence suggests that it might have iatrogenic effects; at worst increasing adverse outcomes such as absconding (Alexander, 2006; Urheim et al., 2011), and at best, increasing recall rates without impacting on recidivism (Drake, 2018; Hyatt & Barnes, 2017; Petersilia & Turner, 1993). As outlined above, there are undoubtedly additional mechanisms that could be introduced to prevent obviously inappropriate candidates being admitted to open conditions, and clearer forward planning in the induction of those of ‘doubtful’ prognosis. But perhaps the most effective way to mitigate risk manifestation in open prison is to develop environments which enable those resident in them to ‘thrive’ (cf. Auty & Liebling, 2020), as well as fostering effective working relationships which enable staff to identify risk manifestation (cf. Dunbar, 1985) and intervene supportively. Yet ultimately, the key objective for HMPPS is to reduce re-offending. Given the low rates of serious recidivistic events in open prisons over time and context (Banks et al., 1975; Dissel, 2008; Hillier & Mews, 2018; Leitch, 1951; Porritt,
1982; see also Chapter 3 results), there is a case for increasing risk tolerance to enable longitudinal formulations of risk to better inform community risk management plans.

**Conclusion**

Open prisons were introduced in England and Wales as a potential solution to a burgeoning prison population and to improve access to employment following long-term incarceration (Smith, 2018). Put simply, they seek to provide a mechanism for supporting successful resettlement and breaking the cycle of offending. Ostensibly, this is what they achieve. Those who spend at least part of their sentence in open prisons in England and Wales are much less likely to re-offend in the community (see Chapter 3). Yet the outcomes for those who get recalled to closed from open prison conditions are comparatively worse, and the recall rate is grossly disproportionate to the risk of both serious recidivistic outcomes in open prison and the community (see Study 2). Effectively – and likely a result of the socio-political climate in which they operate – open prisons are arguably ‘drifting’ from their purpose and becoming principally concerned with mitigating risk exposure over rehabilitation. Indeed, Enhanced Behaviour Monitoring (EBM) as an intervention, has the potential for stabilising behaviour and supporting rehabilitation, yet the potential rehabilitative component is unrealised (see Chapter 4). A cultural shift is required; to change the narrative of open prisons from a peculiarity or oddity of the system, to the important and unique component that they are and should strive to be. Open prison environments should be testing grounds expectant of behavioural aberration, but which provide supportive social climates that encourage rehabilitation (cf. Auty & Liebling, 2020). Their goal should be to reduce community re-offending. Behavioural monitoring protocols such as EBM are, theoretically, well suited to open prison environments. They provide a responsive means for predicting and formulating risk –
particularly given the multifarious methodological issues associated with predicting serious recidivistic events such as abscond (e.g., low base rates, sample selection bias) and both the theoretical (cf. Heffernan et al., 2019a; 2019b) and practical issues (Sweller et al., 2016) in applying nomothetic assessments of risk. However, the potential within EBM to formulate and prepare prisoners for release has yet to be realised and surely, if HMPPS are committed to reducing community re-offending, this must be the direction of travel.
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Appendices

A: National Research Council (NRC) Ethical Approval

APPROVED SUBJECT TO MODIFICATIONS – HMPPS RESEARCH

Mr Gary Goodley
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15th December 2017

Ref: 2017-331
Title: Targeting and Evaluating a Behavioural Monitoring Process Designed to Improve the Risk Management of Prisoners in the Open Prison Estate.

Dear My Goodley

Further to your application to undertake research across HMPPS, the National Research Committee (NRC) is pleased to grant approval in principle for your research. The Committee have suggested the following modifications to the analytic approach and reporting:

- Given that the systematic review could flag up potential predictors that are not in the case file data, consideration should be given to accessing predictors through a Police National Computer data request, or through a request to centrally held OASys data to fill the gaps. Please inform the NRC if such modifications to data access are required during the course of this research.
- For Study 2, a logistic regression is proposed to account for variance explained in a predictive model. Given that discriminant function analysis is more powerful than logistic regression, and can tolerate small sample sizes, the Committee recommends that consideration should be given to using this approach (if the assumptions required for discriminant function analysis can be met).
- For Studies 3 and 4, please also report risk ratios by including additional relative risk analysis. The Committee viewed a risk ratio as more operationally meaningful and accessible to the business than the reporting of odds ratios or similar.

Before the research can commence you must agree formally by email to the NRC (National.Research@NOMS.gsi.gov.uk), confirming that you accept the modifications set out above and will comply with the terms and conditions outlined below and the expectations set out in the HMPPS Research Instruction (https://www.gov.uk/government/organisations/her-majestys-prison-and-probation-service/about/research).
Please note that unless the project is commissioned by MoJ/HMPPS and signed off by Ministers, the decision to grant access to prison establishments, National Probation Service (NPS) divisions or Community Rehabilitation Company (CRC) areas (and the offenders and practitioners within these establishments/divisions/areas) ultimately lies with the Governing Governor/Director of the establishment or the Deputy Director/Chief Executive of the NPS division/CRC area concerned. If establishments/NPS divisions/CRC areas are to be approached as part of the research, a copy of this letter must be attached to the request to prove that the NRC has approved the study in principle. The decision to grant access to existing data lies with the Information Asset Owners (IAOs) for each data source and the researchers should abide by the data sharing conditions stipulated by each IAO.

Please note that a HMPPS/MoJ policy lead may wish to contact you to discuss the findings of your research. If requested, your contact details will be passed on and the policy lead will contact you directly.

Please quote your NRC reference number in all future correspondence.

Yours sincerely,

Dr Sima Sandhu
On behalf of the National Research Committee
**National Research Committee - Terms and Conditions**

**All research**

- **Changes to study** - Informing and updating the NRC promptly of any changes made to the planned methodology. *This includes changes to the start and end date of the research.*

- **Dissemination of research** - The researcher will receive a research summary template attached to the research approval email from HMPPS. This is for completion once the research project has ended (ideally within one month of the end date). The researcher should complete the research summary document for HMPPS (approximately three pages; maximum of five pages) which (i) summaries the research aims and approach, (ii) highlights the key findings, and (iii) sets out the implications for HMPPS decision-makers. The research summary should use language that an educated, but not research-trained person, would understand. It should be concise, well organised and self-contained. The conclusions should be impartial and adequately supported by the research findings. It should be submitted to the NRC. Provision of the research summary is essential if the research is to be of real use to HMPPS.

- **Publications** - The NRC (National.Research@NOMS.gsi.gov.uk) receiving an electronic copy of any papers submitted for publication based on this research at the time of submission and at least one month in advance of the publication.

- **Data protection** - Researchers must comply with the requirements of the Data Protection Act 1998 and any other applicable legislation. Data protection guidance can be found on the Information Commissioner’s Office website: [http://ico.org.uk](http://ico.org.uk). Researchers should store all data securely and ensure that information is coded in a way that maintains the confidentiality and anonymity of research participants. The researchers should abide by any data sharing conditions stipulated by the relevant data controllers.

- **Research participants** - Consent must be given freely. It will be made clear to participants verbally and in writing that they may withdraw from the research at any point and that this will not have adverse impact on them. If research is undertaken with vulnerable people – such as young offenders, offenders with learning difficulties or those who are vulnerable due to psychological, mental disorder or medical circumstances - then researchers should put special precautions in place to ensure that the participants understand the scope of their research and the role that they are being asked to undertake. Consent will usually be required from a parent or other responsible adult for children to take part in the research.

- **Termination** - HMPPS reserves the right to halt research at any time. It will not always be possible to provide an explanation, but HMPPS will undertake where possible to provide the research institution/sponsor with a covering statement to clarify that the decision to stop the research does not reflect on their capability or behaviour.
Research requiring access to prison establishments, NPS divisions and/or CRCs

- **Access** – Approval from the Governing Governor/Director of the establishment or the Deputy Director/Chief Executive of the NPS division/CRC area you wish to research in. (Please note that NRC approval does not guarantee access to establishments, NPS divisions or CRC areas; access is at the discretion of the Governing Governor/Director or Deputy Director/Chief Executive and subject to local operational factors and pressures). This is subject to clearance of vetting procedures for each establishment/NPS division/CRC area.

- **Security** – Compliance with all security requirements.

- **Disclosure** – Researchers are under a duty to disclose certain information to prison establishments/probation provider. This includes behaviour that is against prison rules and can be adjudicated against, undisclosed illegal acts, and behaviour that is potentially harmful to the research participant (e.g. intention to self-harm or complete suicide) or others. Researchers should make research participants aware of this requirement. The Prison Rules can be accessed here and should be reviewed:
  
B: Form UPR16 Ethical Declaration

**FORM UPR16**  
Research Ethics Review Checklist  
Please include this completed form as an appendix to your thesis (see the Research Degrees Operational Handbook for more information)

<table>
<thead>
<tr>
<th>Postgraduate Research Student (PGRS) Information</th>
<th>Student ID: UPR897947</th>
</tr>
</thead>
<tbody>
<tr>
<td>PGRS Name:</td>
<td>Gary Goodley</td>
</tr>
<tr>
<td>Department:</td>
<td>Psychology</td>
</tr>
<tr>
<td>First Supervisor:</td>
<td>Dominic Pearson</td>
</tr>
<tr>
<td>Start Date:</td>
<td>February 2017</td>
</tr>
<tr>
<td>Study Mode and Route:</td>
<td>Part-time ✓</td>
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<tr>
<td></td>
<td>Full-time ✓</td>
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<tr>
<td></td>
<td>MPhil</td>
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<td>MD</td>
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<td>Professional Doctorate</td>
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</tbody>
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| Title of Thesis: Targeting and Evaluating a Behavioural Monitoring Process Designed to Improve the Risk Management of Prisoners in the Open Prison Estate |
| Thesis Word Count: 38,338 |

If you are unsure about any of the following, please contact the local representative on your Faculty Ethics Committee for advice. Please note that it is your responsibility to follow the University’s Ethics Policy and any relevant University, academic or professional guidelines in the conduct of your study. Although the Ethics Committee may have given your study a favourable opinion, the final responsibility for the ethical conduct of this work lies with the researcher(s).

<table>
<thead>
<tr>
<th>UKRIO Finished Research Checklist:</th>
</tr>
</thead>
<tbody>
<tr>
<td>(If you would like to know more about the checklist, please see your Faculty or Departmental Ethics Committee rep or see the online version at: <a href="https://ukrio.org/publications/code-of-practice-for-research">https://ukrio.org/publications/code-of-practice-for-research</a>)</td>
</tr>
</tbody>
</table>

| a) Have all of your research and findings been reported accurately, honestly and within a reasonable time frame? | YES | NO |
| b) Have all contributions to knowledge been acknowledged? | YES | NO |
| c) Have you complied with all agreements relating to intellectual property, publication and authorship? | YES | NO |
| d) Has your research data been retained in a secure and accessible form and will it remain so for the required duration? | YES | NO |
| e) Does your research comply with all legal, ethical, and contractual requirements? | YES | NO |

**Candidate Statement:**  
I have considered the ethical dimensions of the above named research project, and have successfully obtained the necessary ethical approval(s)  

**Ethical review number(s) from Faculty Ethics Committee (or from NRES/SCREC):** NRC 2017-331

If you have not submitted your work for ethical review, and/or you have answered ‘No’ to one or more of questions a) to e), please explain below why this is so:

**Signed (PGRS):**  
**Date:** 30/01/2023

UPR16 – April 2018