Improving Prediction of Potential for Treatment Completion at Tai Aroha

A thesis

submitted in fulfilment

of the requirements for the degree

of

Master of Science (Research) in Psychology

at

The University of Waikato

by

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THE UNIVERSITY OF
WAIKATO
Te Whare Wānanga o Waikato

2023

Abstract

Participant non-completion can be a major problem for treatment programmes. Staff may try to minimise non-completion by deciding who to select for treatment using professional intuition and referral information. It can be difficult for treatment staff to make these decisions regarding the potential for programme completion due to a lack of clear guidelines about what information to consider. This lack of clear guidelines can increase susceptibility to biases, and lead to unreliable and potentially inaccurate decisions. Research has identified 'simple rules' that are tools to aid decision-making quickly, effectively, and consistently. Therefore, using past treatment data, we[1] aimed to identify predictors of programme completion vs. non-completion at Tai Aroha—a residential treatment programme based in Hamilton—to explore whether a "simple rule" can be developed from information readily available at the time of referral, to support staff decision-making when selecting offenders to attend treatment, with the potential to increase programme completion. We were successful in the development of a simple rule to aid Tai Aroha staff selection decisions. The implications, and limitations of our rule and our study are discussed, and future research relating to simple rules are identified.

Keywords: Treatment, programmes, attrition, simple rule, correctional rehabilitation, assessment, selection

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[1] The present research conducted is my own, but I use the term "we" throughout to reflect that this research was conducted in a lab setting and I received advice from my supervisor (Professor Devon Polaschek). Elsewhere, I use the word "we" to refer to what is known/unknown in the wider scientific community.

Acknowledgements

First, I want to acknowledge the support, professional expertise and guidance of my supervisor Professor Devon Polaschek. Thank you for guiding and encouraging me throughout this research. I have learned so much from you and I could not have either completed this work, nor completed it to this standard, without your support, critical eye, your commitment to excellence and my learning and your wise advice. Thank you also to the Ara Poutama Aotearoa and Tai Aroha for supporting this research and providing the data to make it happen, and to Glen Kilgour at Tai Aroha for entrusting me with this important and meaningful research topic.

I would also like to give thanks to all the students in the Polaschek lab at the University of Waikato for all your support, encouragement and feedback. A special thanks to Sam Taaka for your guidance, help and always being there with a listening and supportive ear. Finally, a huge thank you to my family, especially to my mum and my grandad (Gavin) for all your support and encouragement over the past year.

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Offender treatment programmes have a major problem with non-completion or attrition. High non-completion rates across programmes cost the criminal justice system significantly as the system invests both financial and human resources into programme participants. The literature has identified several predictors of treatment attrition including criminal history variables and demographic information. Current practices at Tai Aroha—a residential treatment programme based in Hamilton—to minimise treatment attrition, include staff using their professional intuition and referral information provided about potential participants. Decisions based on intuition lack clear rules or guides increasing susceptibility to biases, which makes the current treatment selection process unreliable even for experienced professionals. Staff currently have no simple or efficient way to support their intuitive decisions to optimise programme retention. This gap shows a need for further identification of attrition predictors and a tool to support staff decision-making. Therefore, we aim to identify predictors of programme completion vs. non-completion at Tai Aroha. Then we will attempt to develop a "simple rule" to support staff decision-making when selecting offenders to attend treatment, potentially increasing programme completion.

Attrition

Problem

Offender attrition rates vary across treatment programmes, with many programmes suffering from high numbers of participants leaving prematurely. High rates of treatment attrition have impacts on offenders (Stokes et al., 2009), on practitioners (Wormith & Olver, 2002), and on the correctional system (Mossière & Serin, 2014). To understand the extent of the impact we must first define the issue. Treatment attrition is defined as those who leave treatment before the end of a programme or intervention, either voluntarily or due to other factors (e.g., being transferred to another correctional facility; Polaschek, 2010). Wormith and

Olver (2002) proposed three main types of offender programme attrition: (a) client-initiated dropout, (b) staff-based exclusion/expulsion, and (c) administrative exit. Client-initiated dropout occurs when participants voluntarily leave treatment prematurely. Staff-based exclusion occurs when participants are unable to complete a programme because of meeting exclusionary criteria identified by staff (e.g., disruptive behaviour or drug use). Administrative exits involve participants being released or transferred from a programme for reasons out of their control. Administrative exits can include courts overturning convictions, parole boards releasing offenders, or offenders transferring to another prison (Wormith & Olver, 2002). Programme context determines the percentage of each type of attrition (Polaschek, 2010). For example, programme attrition can be influenced by the location of a programme, if attendance is mandatory, or if clients are motivated for treatment (McMurran & Theodosi, 2007). Overall, attrition rates across offender treatment programmes range between 20% and 50% (Wormith & Olver, 2002).

Differences in attrition rates across studies can make comparisons difficult. Some studies calculate attrition from initial contact with offenders (i.e., interview) until programme completion, while others calculate attrition from intake (i.e., the first day of the programme) to treatment end. Regardless, attrition rates are consistently high across programmes resulting in several problems throughout the system (Daly & Pelowski, 2000).

Impact on Offenders

Offenders who complete a programme benefit from the positive effects of treatment, including feeling satisfied and accomplished, having experiences or opportunities to change, and improved quality of life (Kroner et al., 2014). Offenders who drop out prematurely are unable to benefit from treatment, and research has identified that non-completers are among those in greatest need of treatment (Stokes et al., 2009). Treatment non-completers may also be at greater risk of recidivism.

Evidence has pointed out that treatment non-completion predicts recidivism and can be associated with increased recidivism over no treatment at all (McMurran & Theodosi, 2007). In a review of the literature, McMurran and Theodosi (2007) found that treatment non-completers are more likely to reoffend when compared to matched controls who received no treatment. However, treatment non-completers also represent 'harder to treat' participants (Polaschek, 2010), and the characteristics associated with treatment non-completion are the same characteristics that predict recidivism. When compared to treatment completers, non-completers are higher risk (Wormith & Olver, 2002), have higher PCL-SV scores (Psychopathy Checklist-Screening Version; a widely employed screening tool in correctional systems as a predictor of reoffending; Skeem et al., 2009), have a higher number of previous convictions, and are generally younger and less educated (Kroner et al., 2014). Hence, this selective loss of non-completers is due to baseline characteristics that also predict recidivism (Polaschek, 2010). Therefore, those at a higher risk of dropping out of treatment are those who require it the most (McMurran & Theodosi, 2007).

Attrition can also affect other offenders in treatment. Participants who drop out of treatment early leave a place vacant in the treatment group. In closed programmes, this place remains empty resulting in waitlisted offenders missing out on treatment (Kroner et al., 2014). In open or rolling group programmes, if non-completion rates are high, it can be difficult for the group to stabilise. Constant change and instability can negatively impact all treatment participants. In an evaluation of Tai Aroha (a residential treatment programme; the same programme we researched in this study), group members commented feeling "stuck" and frustrated, as they had to keep going over orientation skills when new participants joined (King, 2012). Therefore, treatment attrition not only impacts those who drop out, but it can also have repercussions for others in the treatment group.

Human Resource Costs of Treatment Attrition

The impact of treatment attrition goes further than just impacting participants, as attrition can have adverse impacts on treatment staff. Staff invest a significant amount of their time and resources into potential participants pre-treatment (i.e., assessments and interviews) and during treatment to keep participants engaged. When treatment staff are working hard to keep participants engaged and in treatment, attrition can negatively impact staff motivation, and staff can be demoralised by the inefficient use of their time and resources (Robinson & Little, 1982). Decreased staff motivation can negatively affect the treatment climate and staff-offender relationships (Howells & Day, 2007). With already limited resources, service providers often work for extended periods, past their capacity limits putting pressure and stress on staff, which can result in burnout and absenteeism. These adverse effects on staff can impact clients, as burnout and high staff turnover are associated with offender programme attrition (Garner et al., 2007). These results show the far-reaching impacts of treatment attrition on staff and participants.

Treatment Programmes Are Cost Effective

Research has shown that offender treatment programmes are cost effect and essential for reducing recidivism (Block, 2008). Without treatment, offenders are at higher risk of continuing to cycle through the criminal justice system—a system already stretched for resources—costing the government and taxpayers millions each year (Block, 2008). Cost-to-benefit analyses have produced promising results showing that correctional treatment programmes have the potential to provide benefits that outweigh their costs. For example, if offenders have less contact with the correctional system after completing a programme, it may reduce the future cost of treatment, court appearances, and other resources involved in sentencing (Zane et al., 2023). Getting offenders into treatment, however, is only the first hurdle to financial savings for the criminal justice system. High non-completion rates of offender treatment cost the criminal justice system significantly (Daly & Pelowski, 2000). With already limited places in treatment, if a participant leaves prematurely, it increases the overall programme cost per completer (Polaschek, 2010). These findings emphasise the importance of reducing treatment attrition rates among offender treatment programmes.

When evaluating the impacts and effectiveness of treatment, non-completers are generally excluded (Daly & Pelowski, 2000). The exclusion of treatment non-completers from programme evaluations can inflate the estimated rates of programme cost. For example, an empty place in a programme does not necessarily reduce the overall cost of the programme. It is important to capture attrition information because data regarding predictors and consequences of treatment dropout can provide researchers and staff with information about the cost of dropout. Therefore, identifying characteristics that lead offenders to leave treatment prematurely is important for the development of cost-effective treatment programmes and to reduce the overall cost of attrition on the system (Daly & Pelowski, 2000).

Predicting Treatment Attrition

Predictors of Attrition from Previous Research

Across the literature, researchers have identified several predictors of attrition and clients at higher risk of dropping out (Steketee, 1992). These predictors of attrition have been identified at a client level and a programme administrative level. Although these programme administrative predictors, including staff (e.g., rapport with clients), programme, and organisational characteristics, have not gained the same attention as client characteristics. Research has emphasised that programme predictors may play an important role in premature dropout. For example, court-mandated programmes are associated with higher attrition rates, and programmes that offenders feel are helping them with their needs have lower attrition rates (Craissati & Beech, 2001). Dropout may also signal decreased programme quality, staff relationships, and implementation. Offenders may also leave treatment prematurely due to institution relocation or employment (Daly & Pelowski, 2000). Although programme-level predictors of attrition are important, in this study we focused on client characteristics.

Research has consistently found offender characteristics—both static and dynamic factors—associated with treatment attrition (Konecky et al., 2016; Loeb et al., 2015). Static factors are characteristics unchanged by intervention, these factors include age, number of previous convictions, and ethnicity (Wormith & Olver, 2002). In contrast, dynamic factors change over time and can be changed by intervention. For example, treatment can target and change antisocial behaviours and peers (Kroner et al., 2014). Most previous work has looked at a mix of static and dynamic factors that can predict treatment attrition. A meta-analysis of the attrition literature found that increased treatment non-completion is associated with demographic variables, criminal histories, clinical variables, and offender motivation. Demographic variables associated with treatment attrition include lower education levels, single/unmarried, unemployment, lower income, being younger, and having an ethnic minority status (Olver et al., 2011). Criminal histories such as higher rates of previous offences, shorter sentence lengths, and prior violent offences are strongly associated with treatment non-completion (Jewell & Wormith, 2010). Substance abuse and psychopathy have proven to be consistent clinical predictors of non-completion, although the strength of the associations depends on various other variables (e.g., comorbidity; Daly & Pelowski, 2000). Studies have also found offender treatment motivation, readiness, and engagement to be significant predictors of dropout (Drapeau et al., 2005; Howells & Day, 2007). Daly and Pelowski (2000) commented that non-completers are more likely to have no children compared to completers. Wormith and Olver (2002) stated that non-completers are under-educated, unemployed, high-risk offenders and generally classified as maximum security. The predictors above may be important to consider when selecting participants and evaluating programmes to help retain participants and improve programme quality.

Selecting Offenders for Treatment

When selecting participants for treatment, staff could use these previously identified predictors to aid their decisions to help identify those at a higher risk of treatment attrition. However, during pre-treatment selection, staff may only have access to pre-treatment variables, such as offender criminal histories and demographic variables. Kraemer et al. (1998) specifically looked at pre-treatment predictors of attrition and found that out of the seven hypothesised variables (age, defensiveness, impulsivity, criminal prosecution, sexual knowledge, psychological maladjustment, and obsessions and fantasies), only age and impulsivity could predict treatment attrition during the pre-treatment phase. Edwards et al. (2007) also used pre-treatment variables to predict treatment attrition and found twenty-three significant variables. The significant variables included a range of static and dynamic characteristics, such as aggression, diagnosed emotional disorder, impulsivity, and prior convictions. The strongest association was found between attrition and prior convictions.

Static variables such as age and ethnicity have proven to be inconsistent predictors of attrition (Daly & Pelowski, 2000). Some studies found younger age to be a significant predictor (Carl et al., 2020; Konecky et al., 2016) of attrition, while others found no difference in age associations between those who drop out and those who complete treatment (Polaschek & Dixon, 2008). In their review of the literature on predictors of dropout, Daly and Pelowski (2000) stated only two out of nine studies found race or ethnicity to be a significant predictor of dropout. Many studies on treatment attrition yield small sample sizes, this may explain the inconsistencies of predictors across studies. This lack of consistency amongst these predictors makes it difficult for researchers and treatment staff to confidently make changes to selection processes based on these predictors (Steketee, 1992). Selection processes and criteria are important for selecting suitable treatment participants, but these processes can be hard to validate with inconsistent predictors.

Selection Criteria for Treatment

Many treatment programmes include selection criteria to target and select suitable clients for treatment and to avoid dropout (Carl et al., 2020). Selection criteria requires assessments of offender characteristics, situations, and potential outcomes from treatment (e.g., reduction in recidivism from treatment; Bonta, 2002). Treatment staff select offenders for treatment based on the selection criteria and information provided in referrals. After filtering out those who do not meet the criteria, staff are then guided by professional experience and intuition to make further judgements about who to select (Bonta & Andrews, 2007). However, these decisions based on intuition can be susceptible to biases, which limits the current selection process (Nicholls et al., 2013).

Assessments made based solely on professional opinion, intuition, and clinical experience are labelled as unstructured judgements. The literature has proven that unstructured judgements lack clearly defined guidelines for decision-makers, which can increase susceptibility to biases, limiting the reliability and validity of these decisions (Nicholls et al., 2013). Instead, structured assessments using professional guidelines and rules, known as structured professional judgements (SPJ), have proven superior to unstructured decision-making approaches. Human judgments are best when assisted by either an algorithm or algorithmic psychological assessment tool (e.g., actuarial risk assessment) accompanied by other information (e.g., predictors of a desired outcome; Wertz et al., 2022). Therefore, a decision support tool may be beneficial for treatment staff to select offenders who will benefit most from treatment and are less likely to drop out.

The treatment attrition literature has already developed several scales, checklists, and prediction models that could be used as decision-support tools by treatment staff. For example, the Treatment Readiness Scale (TRRS; Serin, 1998) has shown good predictive validity of treatment engagement and dropout. The TRRS is based on pre-treatment assessments of risk and need, treatment readiness, and treatment participation; although the use of information that may not be available to treatment staff when selecting offenders such as treatment participation significantly limits the use of this tool (Serin, 1998). Another example is the Treatment Motivation Questionnaire (TMQ; Ryan et al., 1995), which has proven valuable in predicting treatment dropout. The TMQ was developed to assess internalised and external motivations for treatment before entering a programme and has demonstrated that motivation was predictive of treatment involvement and retention (Ryan et al., 1995). Although, in some cases, offenders say they are motivated and ready for treatment in the hopes it will get them out of prison; this makes motivation and treatment readiness an unreliable measure.

Nunes et al. (2010) developed a simple screening measure for predicting the risk of offender treatment dropout. The authors found that age, motivation for intervention, Statistical Information of Recidivism – Revised 1 (SIR-R1) scale category, marital/family, and attitude were significant predictors of dropout in their sample: combined these items made up the Dropout/expulsion Risk Screen (DRS). The SIR-R1 is an actuarial risk instrument for general recidivism. The DRS items were collected during the initial intake by parole officers. Total scores ranged between -5 and +6 with higher values indicating an increased risk of attrition. Although the DRS has practical uses in the criminal justice system, the false positive rate of the tool was high. Seventy-two percent of the sample were classified as high risk of dropout, even though they completed treatment (Nunes et al., 2010). This can be problematic for offenders who need treatment and may go on to complete it, but miss out on a place in the programme due to producing a high-risk score on the DRS.

Nunes and Cortoni (2006) attempted to develop a screening measure for the risk of dropout among Aboriginal offenders in Canada. The authors decided to examine Aboriginal offenders separately from non-Aboriginal offenders due to their dropout rates being higher. These offenders also received different risk measures than non-Aboriginal offenders. The authors also thought it beneficial to develop a specific measure for Aboriginal offenders to increase confidence with this group. The Aboriginal Dropout Risk Screen (ADRS) was made up of three variables: age, community functioning, and motivation for intervention. Although the ADRS resulted in low predictive accuracy, this is an important step in the development of risk measures and screening tools for use in the criminal justice system (Nunes & Cortoni, 2006). Ethnic minorities and Indigenous people are overrepresented in prison populations around the world (Penal Reform International, 2022), making specific tools for these populations crucial. In Aotearoa New Zealand, Māori make up over 50% of the prison population (Department of Corrections, 2023) despite only comprising 15% of the general population. The use of Westernised tools developed in the absence of cultural consideration has long proven to be detrimental to the healing and rehabilitation of Māori (Muriwai et al., 2015). Any further development or research of tools used on the prison population must consider the needs of Māori.

Simple Rule

Browne et al. (1998) developed a model that successfully predicted attrition. The model used nine variables including childhood history, criminal history, and in-treatment factors that were significantly different between completers and non-completers. Edwards et al. (2007) created a scale with 20 pre-treatment items that predicted attrition. Both of these models are complex with multiple predictors and may require the help of technology and extra time for staff to consider and filter through all the different items. This extra time and technology could be problematic in a field setting where decision-makers must often select a course of action with limited time, insufficient information, and without help from technology (Jung et al., 2020). In these situations, researchers have proposed *simple rules* to aid decision-making, where staff employ simple and effective data-driven methods. Simple rules have a small number of items (e.g., two or three) and can be used to inform decisions without specific training, calculations, or a computer (Kahneman et al., 2021). Jung et al. (2020) proposed a series of simple rules developed from data that took the form of a short checklist. Using one example of judges making bail decisions, the authors developed a simple two-item model. The model included younger age (< 25) and a history of failing to show for trial. The simple two-item model significantly outperformed unassisted decisions made by judges (Jung et al., 2020). Therefore, a simple rule may be helpful to assist staff in making timely decisions about treatment participants to help increase programme retention.

The Current Study

Past research has identified that treatment attrition rates are consistently high across programmes, and can adversely impact participants, staff, and the criminal justice system. Research has also shown there is currently a lack of an efficient and simple way to support staff decision-making and optimise programme retention. We aimed to identify predictors of those who subsequently completed the Tai Aroha program based on pre-treatment variables.

Tai Aroha is a residential therapeutic community based in Hamilton for high-risk violent men serving community sentences (i.e., home detention). Men who met the criteria for the Tai Aroha programme have extensive histories of trauma, crime, violence, gang membership, drug problems, and broken whānau (family) relationships. Some thrive in their time at Tai Aroha, while some are less willing or able to adapt to the challenges of the programme resulting in premature dropout. The Tai Aroha programme has a limit of ten places at one time, and only three in every five participants who starts the programme complete it (King, 2012). Ara Poutama Aotearoa (Department of Correction) staff work through many referrals to identify men who show the most potential to engage and complete the programme. Although many referrals are screened out easily based on criteria (e.g., demographic location or alcohol use), referrals for Tai Aroha significantly outnumber the places available, and those who start the programme are only a small number of all of the men who met the criteria for admission. With high attrition rates, the programme costs the correctional system significantly in human resources, as staff invest their time and effort into selecting and treating the men, and in financial resources with the cost per completer increasing for every non-completer (King, 2012). There are currently no decision support tools in use by Tai Aroha programme staff to triage such a large number of referrals or to alert staff to referred men who may be at a higher risk of not completing treatment.

If we successfully identified promising predictors of treatment completion vs. non-completion among our sample of Tai Aroha participants, our secondary aim was to develop a simple rule to support the decision-making of Tai Aroha staff in selecting men to attend the Tai Aroha treatment programme.

Method

Sample

Our research involved archival data supplied by Ara Poutama Aotearoa of 258 men who started the Tai Aroha programme between 2010 and 2023. Table 1 contains the demographic and programme information of our sample. The average age was 30 at entry to Tai Aroha. Programme data showed over half of the sample (61.6%) completed the programme and the remaining 38.4% did not. Just under three months was the average number of days spent in the programme; the Tai Aroha programme can vary in length depending on the client’s needs. Of those who did not complete treatment the average number of days spent in the programme was 49. All the men in our sample spent time on remand (in custody while they await their trial/sentencing), and 91.4% spent time as a sentenced prisoner in the 5 years prior to Tai Aroha start. Table 1 shows the lead offences of the sample, which documents the offence for each participant that resulted in the longest current prison sentence. Most of the sample were convicted of violent offences, and over half of the sample had a family harm offence. A large proportion of the sample were on home detention sentences. The average RoC*RoI (risk of conviction multiplied by risk of imprisonment) score for the men in our sample is in the high range (> .70) and indicates that, on average, the likelihood of reoffending and returning to prison in the next five years is predicted to be 71%.

Table 1

Sample Characteristics

Characteristic	*N*	Min	Max	*M* (SD) or %
Age		20	55	31.3 (6.8)
Completed	159			61.6
Not completed	99			38.4
Number of days in programme		3	154	88 (37.1)
RoC*RoI score		0.23	0.93	0.71 (0.10)
Gang affiliation	140			54.3
The lead offence for the current sentence				
Breaches	4			1.6
Burglary	46			17.8
Dishonesty	18			7
Drugs	5			1.9
Other	34			13.2
Property	2			0.8
Traffic	16			6.2
Violence	125			48.4
Weapons	8			3.1
Family harm offence	134			51.9
Aggregate violent offence	187			72.5
Aggregate family harm offence	162			62.8

Ever had a family harm offence	222			86
Had any previous community based sentences	248			96.1
Number of previous community sentences		0	24	5.1 (4.4)
Had any previous custodial sentences	257			99.6
Number of previous custodial sentences		0	28	6.5 (4.4)
Spent time on remand	258			100
Number of days spent on remand		1	1266	270.1 (203.2)
Spent time as a sentenced prisoner	236			91.4
Number of days spent as a sentenced prisoner		0	8539	684.2 (992.5)
Count of history of custodial misconduct charges		0	38	4.37 (4.6)
Count of history of custodial incidents		1	142	17.9 (22.2)
Count of history of custodial alerts		1	33	7.3 (4.2)
Current sentence length		13	730	200.1 (127.7)
Current sentence type				
Home detention	228			88.4
Intensive supervision	26			10.1
Parole	1			0.4
Released on conditions	2			0.8
Supervised	1			0.4
Treatment exit reasons for non-completers				
Ceased because of poor responsivity	1			0.4
Evicted, misconduct, or absconded	22			8.5
Exited without a reason	7			2.7
Reason not recorded	31			12
Outcome not achieved	37			14.3
Withdrew for personal reasons	1			0.4
Days to treatment exit for non-completers		3	156	49 (37.14)

Note. $N = 258$. All variables captured in the five years prior to Tai Aroha start.

Ara Poutama Aotearoa provided us with a dataset of 43 variables for each participant in the sample. Six variables captured programme information (e.g., start date and completion status), 33 variables involved sentence and prison information (e.g., sentence length and lead offence); this also included information regarding misconduct charges, incident involvement (either victim or perpetrator in the incident), and history of active alerts (a flag or notification about an offender; e.g., history of staff assault or risk of escape) for each participant in the five years before Tai Aroha entry. The remaining four variables described participants' demographic information (e.g., age and RoC*RoI score). Table 2 outlines some of the variables supplied to us, see Appendix A for a list of all variables and definitions.

Table 2

List of Variables and Descriptions from Data Supplied by Ara Poutama Aotearoa.

Variable name	Description
Demographic variables	
Offender ID	Unique identifier for each participant
Age	Age at the commencement of sentence
RoC*RoI score	Statistical assessment of the likelihood of reoffending and reimprisonment within five years.
Gang affiliation	Whether the offender is associated with a gang or not*
Prison/sentence related variables	
Directive type	Type of sentence or active order
Lead offence	Offence for which the most severe penalty imposed
Aggregate violent offence	If there were any other active violent offence during the same sentence*
Number of previous community sentences	Count of all past community-based sentences
Number of days spent on remand	Number of days spent in remand custody (in custody while they await their trial/sentencing) in the past five years
Alerts	
Risk of self-harm	Prisoner is/has been at risk of self-harm
Segregation	Prisoner is/has been separated from other prisoners
Segregation section 58	Prisoner separated for purposes of security, good order, or safety of themselves or others
Transport	

	Prisoner has requirements during transport (e.g., not to be placed with another prisoner)
Misconduct	
Assaults or fights	Assaults, or fights with, any other person
Behaves offensively	Behaves in an offensive, threatening, abusive, or intimidating manner
Disobeys lawful order	Disobeys any lawful order of an officer/staff member, or disobeys or fails to follow any regulation made under the Corrections Act or any rule of the prison made under section 33
Incident	**Example**
Prisoner behaviour	Fighting, prisoner verbally abuses/threatens staff
Prisoner management	Handcuffs, receives bad news, threatens self-harm
Prisoner safety/well-being	Self-harm – no threat to life, illness
Programme Variables	
Start date	Entry into Tai Aroha
End date	The end date of Tai Aroha
Completed indicator	Indication of completion*
Exit reason	Text reason for exiting the programme

Note: Variables all captured at the time of Tai Aroha start. * = dichotomous variable (1 = yes, 0 = no).

Data Preparation

To prepare data for analyses we first identified any missing data. The initial dataset (*N* = 315) included 7 participants who were currently completing the Tai Aroha programme (i.e., they had missing programme end dates), we excluded these participants as we could not determine whether they would complete the programme or not. Five participants were missing several variables each, including age, lead offence, gang affiliation, and directive type; we excluded these five cases. Four cases were missing information regarding aggregate offences and family harm offences; any analyses using these variables excluded the missing cases. We also identified 27 participants who entered the programme twice. We decided to remove the 27 participants' second attempt at the programme because staff could recognise returning participants when doing assessments, and staff could use prior personal knowledge about a participant to make decisions. We also removed 20 participants who were under 20 years old at the time they started Tai Aroha, as staff advised they do not take under 20 referrals anymore.

Most of the variables supplied were continuous variables (e.g., sentence length in days), we recoded these variables into dichotomous variables as recommended by Jung et al. (2020). The age variable was dichotomised at 25 years ($0 = 20$ to 24, $1 \geq 25$) as advised by Ara Poutama Aotearoa staff based on their standard age groupings. The dataset provided us with a dichotomous completion variable that indicated each participant's completion status (0 = non-completion, 1 = completion).

Data Analysis Plan

We used IBM SPSS V.26 and R version 4.2.2 to analyse all data. We ran preliminary analyses to calculate descriptive statistics. Cross tabulations were used to analyse associations between the predictor variables and the outcome, and to identify suitable variables for further analysis. All analyses used the completion status (i.e., 0 = non-completer and 1 = completer) as the grouping variable. We analysed all of the variables provided to understand their relationship with treatment completion. We only used predictor variables with significant associations with the outcome in further analyses.

We then used best subset logistic regression analyses, to further investigate if we could develop a simple rule from the significant variables identified in preliminary analyses. Simple rules are data-driven models that contain a small number of items and can be used to inform decisions without the use of complex training, calculations, or technology (Kahneman et al., 2021). Best subset logistic regressions identify the best models based on all possible combinations and numbers of predictors (Zhang, 2016). We used this approach as opposed to a stepwise or a selection method because it gave us the option of having independently distinct models as the number of predictors (starting with the best single predictor) increased by one, whereas stepwise and selection approaches systematically add predictors resulting in nested models. Akaike information criteria (AIC) and Bayesian information criteria (BIC) were then used to compare and determine models fit for the data, BIC is more appropriate for selecting correct and more parsimonious models (Chakrabarti & Ghosh, 2011; Zhang, 2016).

To protect our models against over-fitting and to test their performance, we cross-validated the models from the regression analysis. We employed a 10-fold cross-validation method, which is used to evaluate models based on a limited sample size by resampling within the same sample (Brownlee, 2023). This approach divides the sample into 80% for training and 20% for testing and tests the model on 10 iterations of the split data. The method works by estimating each model's performance based on pooled data from the first nine out of ten iterations, where the tenth sample is used as the validation sample. The process repeats itself 10 times and the model's performance are estimated by the average across all iterations. The cross-validation statistic, Cohen's kappa, is a type of accuracy statistic that accounts for the base rate of the outcome variable, which is important when the outcome groups are not equal sizes (i.e., more completers than non-completers; James et al., 2013). Landis and Koch (1977) outlined kappa statistic ranges as < .20 = none, .21-.39 = minimal, .40-.59 = weak, .60-.79 = moderate, .80-.90 = strong and > .90 = almost perfect.

We then calculated the area under the receiver operating curve (AUC) statistics for each model. The AUC statistics calculate the probability that a randomly selected completer will have higher scores on the model than a randomly selected non-completer. The scores can range from 0 to 1, with a score of 0.5 indicating predictive accuracy the same as chance. Above 0.5 indicates positive predictive accuracy (i.e., higher scores are associated with a higher likelihood of completion), and below 0.5 demonstrates negative predictive accuracy (i.e., lower scores are associated with a lower likelihood of completion), with scores closer to 1 indicating better accuracy (Helmus & Babchishin, 2017).

Finally, we computed fourfold tables for two of the models. Fourfold tables show the likelihood of the outcome for participants with (completed treatment) and without (did not complete treatment) the outcomes. Visual representations of the relationships between predictors and the outcome can be helpful in decision-making (Hanson, 2022). To create fourfold tables, variables that had a positive relationship with treatment completion were reverse coded (alert for weapons and ANZSOC property and pollution offences), so all of the variables had a negative relationship with the outcome. Fourfold tables allow for the computation of sensitivity and specificity, which are measures commonly used to determine the performance of a test. Sensitivity, or the rate of true positives, shows the model's ability to predict true positives (predict those who complete treatment as positives). Specificity, or true negative rate, shows how well a test predicts true negatives (predict non-completers as negatives). Specificity and sensitivity are considered stable measures of a tool's performance. In contrast to these measures we computed predictive values, which also measure the tools performance but will change with the prevalence of the outcome. For example, the more common treatment completion is the more confidence we can have in the tools ability to indicate a completer and less confidence we have in the tools ability to indicate a non-completer. We computed positive predictive values (PPV) and negative predictive values (NPV) for the models, which show the true proportion of completers and non-completers in the sample and the model's ability to detect them as positives or negatives (Monaghan et al., 2021).

Results

First, we examined the relationships between each predictor variable and treatment completion using cross-tabulations. Overall, 23 dichotomous variables had a significant relationship with treatment completion, shown in Table 3.

Table 3

Significant Chi-square Associations between Dichotomous Independent Variables among Completers vs. Non-completers

Variable	Total	Completer		Non-completer		X^2	*p*	*df*
		n	%	*n*	%			
Alerts								
Forensic concerns	18	6	3.8	12	12.1	6.55	**.01**	1
Risk of self-harm	134	69	43.4	65	65.7	12.11	**<.001**	1
Seg58 1A directed security good order	45	21	13.2	24	24.2	4.15	**.023**	1
Seg60 1B directed mental health	3	0	0.0	3	3.0	4.87	**.027**	1
Segregated	15	3	1.9	12	12.1	11.67	**<.001**	1
Segregated section 58	9	2	1.3	7	7.1	6.12	**.013**	1
Transport	7	1	0.6	6	6.1	6.82	**.009**	1
Under 20	50	21	13.2	29	29.3	10.11	**.001**	1
Weapon	68	49	30.8	19	19.2	4.24	**.039**	1
Young person	9	2	1.3	7	7.1	6.12	**.013**	1
Misconduct								
Assaults or fights	70	30	18.9	40	40.4	14.31	**<.001**	1
Behaves offensively	53	24	15.7	28	28.3	5.89	**.015**	1
Deliberately damages property	45	18	11.3	27	27.3	10.78	**.001**	1
Disobeys any lawful order	90	48	30.2	42	42.4	4.02	**.045**	1
Obstructs any officer	5	0	0.0	5	5.1	8.19	**.004**	1
ANZSOC Category								
Miscellaneous offences	23	9	5.7	14	14.1	5.40	**.02**	1

Property damage and environmental pollution	229	147	92.5	82	82.8	5.66	**.017**	1
Incident role								
Victim	159	84	52.8	75	75.8	13.56	**<.001**	1
Incident type								
Other	58	29	18.2	29	29.3	4.27	**.039**	1
Prisoner behaviour	210	123	77.4	87	87.9	4.46	**.035**	1
Prisoner management	152	85	53.5	67	67.7	5.09	**.024**	1
Prisoner safety/welfare	67	32	20.1	35	35.4	7.36	**.007**	1
Age (under 25)	58	26	16.4	32	32.3	8.93	**.003**	1

Determining the Best Predictor Combinations of Treatment Completion

Next, we further examined the independent variables (Table 3) to identify if we could develop a simple rule. Variables that did not meet the assumptions for logistic regressions were excluded (Stoltzfus, 2011); we removed six variables due to having fewer than 20 observations (alert for forensic concern, alert for segregated section 60 1B directed mental health, alert for segregated, alert for transport, alert for segregated section 58, and misconduct charge for obstructs an officer in execution of their duty). Advice from Tai Aroha staff regarding not taking under 20s also meant we removed the variables, alert for under 20 and alert for a young person from any further analyses. The remaining 15 variables were alerts for risk of self-harm, seg58 1A directed security good order (prisoner separated because security or good order of the prison would otherwise be endangered), and weapon; misconduct charges for assaults or fights, behaves offensively, deliberately damages, and disobeys any lawful order; ANZSOC categories for miscellaneous offences (e.g., defamation or public safety offences) and property/environmental offences; and four incident categories as well as being a victim in an incident. These variables were used in a series of best subset logistic regressions, which identified 15 independent models with different combinations and numbers of variables. Table 4 shows the regression output of each model that was identified.

Table 4

Best Subset Logistic Regression of 15 Independent Variables on Treatment Completion

Model	Variable combination	Variable names	loglikelihood	AIC	BIC
1	1	1. Misconduct assaults or fights	-164.7641	331.5283	335.0813
2	1, 2	2. Victim	-160.055	324.11	331.216
3	1, 2, 3	3. Alert weapon	-155.3282	316.6564	327.3153
4	1, 2, 3, 4	4. ANZSOC miscellaneous	-150.8397	309.6794	323.8913
5	1, 2, 3, 4, 5	5. Alert risk of self-harm	-147.855	305.7101	323.4749
6	1, 2, 3, 4, 5, 6	6. ANZSOC property	-145.0727	302.1454	**323.4632**
7	1, 2, 3, 4, 5, 6, 7	7. Age	-142.7255	299.451	324.3217
8	1, 2, 3, 4, 5, 6, 7, 8	8. Alert seg58 directed security good order	-140.6301	**297.2601**	325.6838
9	1, 2, 3, 4, 5, 6, 7, 8, 9	9. Misconduct deliberately disfigures	-140.0327	298.0654	330.0421
10	1, 2, 3, 4, 5, 6, 7, 8, 9, 10	10. Incident prisoner safety	-139.6536	299.3073	334.8369
11	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11	11. Misconduct disobeys	-139.4449	300.8898	339.9723
12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12	12. Incident prisoner management	-139.288	302.5761	345.2116
13	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13	13. Misconduct behaves	-139.1302	304.2604	350.4489
14	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14	14. Incident other	-139.076	306.152	355.8934
15	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15	15. Incident prisoner behaviour	-139.0378	308.0755	361.3699

Note. N = 258, bolded = AIC and BIC recommended models.

The AIC indicated Model 8 (misconduct for assaults or fights, being a victim in an incident, alert for weapons, ANZSOC category for miscellaneous offences, alert for risk of self-harm, ANZSOC property offences, younger age, and alert for seg58 directed security good order) was the best fit, whereas the BIC indicated model 6 (misconduct for assaults or fights, being a victim in an incident, alert for weapons, ANZSOC category for miscellaneous offences, alert for risk of self-harm, and ANZSOC category for property offences) was best. To test the performance of all of the models we conducted a 10-fold cross-validation. In Table 5, the 10-fold cross-validation results indicate the models performed minimally to fairly (based on Landis and Koch (1977) criteria), with kappa statistics ranging between 0.2 (model 3) and 0.39 (model 7).

Table 5

10-fold Cross-validation of Models 1 to 15

Model	Kappa	Summary of sample sizes for each iteration
1	.24	187, 186, 186, 187, 187
2	.25	186, 186, 187, 187, 186
3	.2	187, 186, 186, 187, 186
4	.28	187, 186, 186, 186, 187
5	.31	187, 187, 186, 186, 186
6	.25	187, 186, 186, 187, 186
7	.39	187, 186, 186, 186, 187
8	.36	187, 187, 186, 186, 186
9	.34	187, 186, 186, 186, 187
10	.31	187, 187, 186, 186, 186
11	.34	187, 186, 186, 186, 187
12	.34	187, 186, 186, 187, 186
13	.33	187, 187, 186, 186, 186
14	.25	186, 186, 186, 187, 186
15	.32	187, 186, 186, 186, 187

Note. 80% of the data was used for testing and 20% was left out for training.

Next, we calculated the predictive accuracy scores for all 15 models. The AUC statistics (Table 6) show that, overall, the models predicted treatment completion better than chance. The models had AUC statistics ranging from 0.61 (model 1) to 0.79 (model 13) and are all significant. The models indicated by the AIC and BIC criteria —model 8 and model 6— have overlapping confidence intervals, meaning they are not significantly different.

Table 6

Area Under the Curve Statistics for all 15 Models of the Best Subset Regression

				95% CI	
Model	AUC	Std. Error	Significance	Lower	Upper
1	.61	.037	.004	.53	.68
2	.66	.035	<.001	.59	.73
3	.69	.033	<.001	.63	.76
4	.71	.033	<.001	.65	.78
5	.74	.031	<.001	.68	.80
6	.75	.031	<.001	.69	.81
7	.76	.031	<.001	.70	.82
8	.77	.03	<.001	.71	.83
9	.78	.03	<.001	.72	.84
10	.78	.03	<.001	.72	.84
11	.78	.029	<.001	.72	.84
12	.79	.029	<.001	.73	.84
13	.79	.029	<.001	.72	.84
14	.78	.029	<.001	.73	.84
15	.78	.029	. <.001	.73	.84

Note. $N = 258$. AUC = area under the curve. Std. = standard. CI = confidence intervals.

Next, to determine the most practical model we computed fourfold tables for models 2 and 3; the rest of the models had very low occurrences (≤ 1) of the outcome (non-completion and completion; base rate). This low occurrence was due to participants lacking the specific combinations of predictors from models 3 to 15. Low base rates can result in the models having high false positives and false negatives, making them invalid as pre-treatment selection models. False positives occur when participants are identified by the model as completers but are non-completers, and false negatives are those identified as non-completers but are completers. As a result, model 2 (a combination of the variables misconduct for assaults/fights and victim in an incident) and model 3 (a combination of the variables misconduct for assaults/fights, was a victim in an incident, and did not have an alert for weapon) were selected for further analysis.

Table 7 shows the fourfold table for Model 2. Of the 159 participants who completed the Tai Aroha programme, 13% (21) of participants had both predictor variables compared to 21% (34) of participants who did not complete the programme, demonstrating participants without a misconduct charge for assaults/fights and those who had not been a victim in an incident were more likely to complete the programme. Model 2 correctly identified completers 13% of the time (sensitivity) and correctly identified failure to complete 65% of the time (specificity). Such a low sensitivity will, however, result in Model 2 having a high false positive rate.

In the sample, 38% (positive predictive value; PPV) had both predictor variables from Model 2 and were a programme completer, and 32% (negative predictive value; NPV) had neither predictors nor completed the programme. These percentages show the actual proportion of completers to non-completers in our sample detected by the model.

Table 7

Fourfold Table of Model 2

Actual completion status	Does not have both predictors	Has both predictors	Total
Non-completer	65	34	99
Completer	138	21	159
	203	55	

Table 8 shows a fourfold table for Model 3. Table 8 shows that of the 159 completers, 6% (10) had all three predictor variables (misconduct charge for assaults/fights, was a victim in an incident, and did not have an alert for weapons), compared to 24% (24 out of 99) non-completers, meaning those without these variables were more likely to complete treatment. Model 3 correctly identified completers 6% of the time (sensitivity), and correctly identified non-completers 75% of the time (specificity). Model 3 also has low sensitivity, indicating a high false positive rate of participants being identified as completers when they are likely non-completers. Model 3 had a PPV of 29%, where participants had all three predictor variables and were programme completers. A total of 33% (NPV) had two or fewer predictors and did not complete treatment, reflecting the actual proportion of positive and negative model scores to completers and non-completers in the sample.

Table 8

Fourfold Table of Model 3

Actual completion status	Does not have all 3 predictors	Has all 3 predictors	Total
Non-completer	75	24	99
Completer	149	10	159
	224	34	

Discussion

This study investigated predictors of treatment completion vs. non-completion among participants who attended the Tai Aroha treatment programme, a rehabilitation facility for high-risk violent men eligible for community sentences. Treatment non-completion or attrition occurred when participants left treatment because of poor responsivity, misconduct, abscondment, or personal reasons. For example, participants dropped out because of drug problems, aggressive behaviour, or mental health barriers. Treatment non-completion also included those who left treatment before intervention was complete or intervention was not achieved (i.e., participants disengaged). Once we identified significant predictors of treatment completion, we then aimed to determine if we could develop a simple rule to help staff make pre-treatment selection decisions that have the potential to increase treatment completion.

Tai Aroha Attrition Rates

Our dataset included all those who started the Tai Aroha programme since it began in 2010 (King, 2012). Of the 258 participants from our final sample, 38.3% (99) did not complete the programme. This result was similar to those from a 2015 evaluation of Tai Aroha, where the non-completion rate was 35.2% (Kilgour, 2015). These findings are in line with other research done on attrition rates among similar samples of high-risk violent men in Aotearoa (30%; Polaschek, 2010). High-risk offenders have more complex needs and longer criminal histories compared to medium and low-risk offenders, making them a tougher group of participants to manage and treat. At Tai Aroha, an evaluation has shown that participants have extensive needs and were highly criminalised (Kilgour, 2015). Attrition rates may have remained consistent over time for a number of reasons including the characteristics of participants or that treatment is not delivered appropriately for a ‘harder to treat’ group (Wormith & Olver, 2002).

The non-completion rate in this study reflects the wider attrition literature, where non-completion across different types of offender treatment programmes ranges between 20-50% (Browne et al., 1998; Brunner et al., 2019; Wormith & Olver, 2002). In a meta-analysis of 114 studies, Olver et al. (2011) found an attrition rate of 27.1% across offender treatment programmes, with a drop-out rate of 37.8% for violence-related programmes. The authors also found higher attrition among community-based programmes than prison-based programmes. With consistently high attrition rates across treatment programmes, it is important to identify predictors of both treatment attrition and completion to allow researchers and programme staff to modify selection and programme delivery with these predictors in mind (McMurran & Theodosi, 2007).

Predictors of Treatment Completion vs. Non-completion

First, we aimed to determine whether we could identify predictors of treatment completion vs. non-completion among those who attended the Tai Aroha programme. We identified 18 predictors of treatment completion vs. non-completion.

Custodial Active Alerts

Treatment completers were less likely to have a historic alert in their custodial file for forensic concern (having contact with the forensic mental health team), risk of self-harm, segregation (separated from the main prison population), segregation for security or good order, segregation for mental health, segregated section 58 (separated because of disruptions to security, good order, or safety of others), transport (e.g., not to be placed with other prisoners during transport), under 20, and young person (under 16 years). The negative relationship between treatment completion and alerts for forensic concern, risk of self-harm, and segregation for mental health aligns with previous findings on predictors of treatment attrition, where non-completers were more likely to have mental health concerns compared to completers (Daly & Pelowski, 2000). Other research also found that non-completers were more likely to have a conduct or emotional disorder and a history of difficulties in school compared to completers (Edwards et al., 2007). These findings represent what we already know about treatment non-completers having more complex needs and mental health issues compared to completers (Wormith & Olver, 2002).

Completers were more likely to have an alert for weapons compared to non-completers. This relationship between alert for weapon use and treatment completion is contrary to past research; Kroner et al. (2014) found that recent weapon use predicted treatment attrition. In their work weapon use was collapsed into a variable labelled recent antisocial behaviour, which also included institutional misconduct and staff assault, making it difficult to understand the independent relationship between weapon use and treatment completion.

Alerts for a young person and under 20 had a negative relationship with treatment completion, and programme completers were more likely to be older (i.e., 25 years and older) compared to non-completers. An alert for young person flags prisoners under the age of 16, and alert for under 20 flags prisoners between 16 and 20 years. This finding was not surprising as prior research has consistently identified younger age as a predictor of treatment non-completion (Browne et al., 1998; Cunha et al., 2022; Howard et al., 2019; Kraemer et al., 1998). Research specifies that those under 25 were more likely to drop out compared to those over 25 (Nunes et al., 2010). This research aligns with our study as our age variable was dichotomised at 25 years, and under 25s in our sample were more likely to be non-completers.

Misconduct Charges

We found treatment completers were also less likely to have a custodial record for misconduct charges for assaults or fights, behaving offensively or threatening, disobeying a lawful order, or obstructing an officer in the execution of their duty when compared to non-completers. These findings align with prior work on treatment attrition, as other research has found that participants with a history of institutional misconduct were more likely to drop out of treatment (Howard et al., 2019; Olver et al., 2011). Non-completers are also more likely to have a history of prison misconduct, where these participants are less compliant with institutional rules and regulations, act more aggressively during treatment, and are generally more criminalised compared to those who completed treatment (Beyko & Wong, 2005). These findings also align with what we know about the Tai Aroha programme, where the men have high levels of criminal thinking and extensive criminal profiles (Kilgour, 2015). Our findings of misconduct charges are consistent with the wider literature that breaking rules, disobeying staff, and being non-compliant with the regulations are predictors of treatment non-completion. Rule-breaking behaviour, non-compliance, and aggression are associated with criminogenic needs. Offenders' criminogenic needs are dynamic factors that play a crucial role in reducing reoffending; targeting these needs during treatment is important for promoting desistance (the process of moving away from crime and offending; Wooditch et al., 2013). These findings emphasise the importance of identifying participants at a higher risk of dropping out to help them succeed in treatment to break the cycle of offending and reduce criminality.

Incident Involvement

Completers were less likely to be the victim of an incident while they were previously in prison; this aligns with victimisation research, where completers were less likely to have a history of victimisation than non-completers (Geer et al., 2001). We also found that completers were less likely to be involved in incidents concerning prisoner behaviour, prisoner management, prisoner safety/welfare, and all other incidents compared to non-completers. The latter incident category involves a variety of different outcomes, ranging from rule-breaking and fighting to illness. The incident category prisoner behaviour involves situations like prisoners fighting, abusing staff, or rule breaking. This aligns with the above research on rule-breaking where non-completers are more likely to be non-compliant and have aggression problems while in prison (Beyko & Wong, 2005). Incidents involving prisoner management involve incidents where handcuffs were needed during movements, control and restraint techniques were employed, or spontaneous use of force was required. This aligns with other Tai Aroha research that non-completers are higher-risk offenders and hard to manage (Kilgour, 2015). The prisoner welfare and safety category included any incident to do with the health and well-being of prisoners and any safety issues. This category includes threats of self-harm, hospitalisation, or involvement in a serious harm situation, confirming non-completers have more complex mental health problems than completers (Olver et al., 2011).

Offence Type

In Aotearoa and Australia, a standardised offence classification framework groups criminal behaviour for use in the analysis of crime and justice statistics. Each offence committed is categorised using the ANZSOC (Australia New Zealand Security Offence Classification). Completers were less likely to have miscellaneous offences (e.g., defamation and privacy offences) as categorised by the ANZSOC and more likely to have property damage and environmental pollution offences than non-completers. Our finding that completers are more likely to have a property offence is contrary to previous research where non-completers were found to be more likely to have a property offence (Jeandarme et al., 2021; Kopak et al., 2015). Although the sample consisted of violent offenders, the ANZSOC category can include aggregate offences (i.e., multiple offences that are part of the same prison sentence) or any past offences. Past research has identified that violent offences and histories of violent offending are promising predictors of treatment attrition (Browne et al., 1998; Wormith & Olver, 2002). In our study, we did not find violent offending predictive. This inconsistency in findings from previous research concerning both property offences and previous violent offending could be because of the specialised nature of our sample, where all the participants were high-risk violent offenders. Our findings do, however, align with research confirming that people who offend are more likely to be generalist offenders, where they are likely to engage in a diverse range of offending behaviours (Elonheimo et al., 2014). Most men in our sample—both completers and non-completers—had a violent lead offence, and most also had at least one aggregate or additional offence. These additional offences show that the men were not specialist violent offenders but rather generalist offenders involved in several different offending behaviours. Our findings substantiate that the men who go into Tai Aroha have extensive criminal profiles and high levels of criminality. (Kilgour, 2015)

With several significant contributors to programme completion vs. non-completion, it reflects that attrition is a heterogeneous process and a variety of different factors can put participants at a higher risk of leaving treatment prematurely (Howard et al., 2019).

Simple Rule

Once we identified promising predictors, we moved on to our secondary aim. Our secondary aim was to determine whether we could develop a simple rule to guide staff decision-making about who is more likely to complete treatment. Tai Aroha staff draw on available information (e.g., current offence, offending history, sexual offending, rehabilitation needs, problem recognition and motivation to change, alcohol and drugs and addiction issues, gang allegiances, mental health issues, intellectual disability, special sentence conditions, other rehabilitation programmes completed, employment, pro-social supports) to make their selection decisions. This selection process currently lacks research showing whether this information is useful or informative to base decisions off. Simple rules are guides that take the form of a short checklist of a small number of significant predictors of the outcome of interest (i.e., treatment completion; Jung et al., 2020). Decisions about who goes into treatment are currently at the discretion of Tai Aroha staff and their professional judgement, which could mean the current selection process is unreliable, because even with referral information, these decision-making processes can be susceptible to biases and errors (Nicholls et al., 2013; Wertz et al., 2022). A data-driven support tool to assist decision-making could help with increasing the reliability of selection decisions by Tai Aroha staff. Our focus was on developing a rule to help staff identify those who have a better chance of completing treatment and also those who are at a higher risk of not completing treatment without additional support. The men going into Tai Aroha are generally supplemented with several resources to help them complete treatment; the identification of potential completers and non-completers will help with resource allocation as those at a higher risk of dropping out may require additional resources to help them succeed (e.g., drug and alcohol counselling, reading aids, or medication). Better allocation of resources and help for those who need it most has the potential to increase treatment completion at Tai Aroha.

Our results indicated that a lack of a misconduct charge for assaults or fights was the most significant independent predictor of treatment completion. Then not being a victim in an incident was the second most predictive variable, and the third most predictive variable of treatment completion was having an alert for weapons. Together these three variables made up Model 3, and Model 2 was composed of the variables lacking a misconduct for assault or fights and not being a victim in an incident. These two models were identified as the most practical to use and implement in a field setting, as they had significant area under the curve scores (Model 2 = 0.66, Model 3 = 0.69) showing promising predictive ability and had high enough base rates of the outcome. Models 2 and 3 also had only a small number of predictors, which is important for simple rule development as fewer items allow staff to apply the rules mentally with limited information (Jung et al., 2020). Once these models were computed into fourfold tables (Tables 7 and 8), we were able to compare and determine the models' abilities to correctly classify completers and non-completers.

Model Comparison

Models 2 and 3 have different advantages and disadvantages. The models were compared based on specificity and sensitivity values as well as predictive values. Sensitivity and specificity are inversely related, meaning a higher score on one will result in a lower score on the other. This means deciding which one is more important will help to identify the most relevant model (Parikh et al., 2008). For example, if identifying completers is more important than identifying non-completers then the model with higher sensitivity will be more desirable, whereas if identifying non-completers is more important the model with higher specificity will be best. Model 2 has a slightly lower specificity than Model 3 and a higher sensitivity, meaning that Model 2 is better at correctly identifying completers but is less accurate at identifying non-completers. This model would result in non-completers being incorrectly identified and missing out on the preparatory resources they need to succeed. Model 3, on the other hand, has a higher specificity and lower sensitivity than model 2, resulting in model 3 being more accurate in identifying non-completers but less accurate at identifying completers.

The consequences of incorrectly identifying completers or non-completers include both human and resource costs for the correctional system. If potential completers are incorrectly classified as higher risk of non-completion and therefore require more support, it could lead to them using up preparatory resources when they are not needed as the participants would have completed anyway. With already limited resources in offender treatment programmes, this could cost the system in both finances to supply resources and staff time (Garner et al., 2007). Inaccurately identifying completers as non-completers could also result in potential completers missing out on treatment as staff may identify other participants who are seen to be better suited for treatment. Participants missing out on treatment because a decision tool deemed them as non-completers when they would have most likely gone on to complete treatment is problematic. Other research on treatment attrition has argued that instead of using results to exclude participants from treatment or to develop an 'attrition profile', they should be used to help those identified as higher risk and to inform practitioners of programme improvements (Beyko & Wong, 2005).

Predictive values for each model show us how well the test is performing (Parikh et al., 2008). Positive predictive values (PPV) reflect the actual number of participants with the predictors of each model and who completed treatment. Model 2 had a positive predictive value of 38%, meaning 38% of participants were identified as completers by the model and were actually treatment completers. Model 3, on the other hand, had a PPV of 29%. Positive predictive values are important for telling us how many predicted vs. actual positive test scores there are: the higher the number the more accurate the model. Both models have relatively low positive predictive accuracy. Model 2 had a better proportion of predicted vs. actual positive test scores. Negative predictive values (NPV) show the actual number of participants that had neither predictors of each model and were non-completers; like PPV the higher the number the better the model. Model 2 had an NPV of 32%, meaning 32% of participants were identified as non-completers by the model and were actually non-completers, and Model 3 had an NPV of 33%. Models 2 and 3 had very similar NPV, where the number of predicted vs. actual negative test scores between the models differed by 1% (Parikh et al., 2008). The predictive values show that Model 2 is the preferred test as it had a higher percentage of true positives than Model 3, and the models did not differ in NPV.

Based on the comparison of models 2 and 3, it is clear there are trade-offs for employing either of the models as a decision support tool. Based on the advantages and disadvantages of each model, it would be more beneficial to use Model 2 to help staff make decisions about who may be more likely to complete treatment. Model 2 is better at identifying completers and less accurate at identifying non-completers, which would result in more completers being selected for treatment compared to if Model 3 was used. Although Model 2 is less accurate at identifying non-completers, it is less likely to result in completers missing out on treatment because they were labelled as potential non-completers. Model 2 would also result in fewer preparatory resources used up on those who do not need them as fewer completers would be incorrectly identified for additional support.

The simple rule that we have developed is a combination of the variables: an offender's custodial history of a misconduct charge for assaults/fights and whether the offender was a victim in a custodial incident. When making decisions about treatment participants, referred men with the presence of both variables are at a higher risk of not completing treatment.

Implications

Practical. Our results have provided empirically driven predictors of treatment completion. Based on these predictors, we developed a practical tool—in the form of a simple rule—to help support staff decision-making. Our simple rule included two variables: misconduct charge for assaults/fights and being a victim in an incident. Staff can use these two variables in combination to identify if referred men are at an increased risk of not completing treatment. The current selection process at Tai Aroha is based on staff professional judgement. Research has identified that any assessments or decisions made based on professional intuition are unreliable and can be biased. Instead using data-driven guidelines or rules has proven to outperform unassisted decisions (Nicholls et al., 2013; Wertz et al., 2022). The simple rule we developed can help staff identify those who are at an increased risk of not completing treatment before starting a programme, helping staff to determine who will benefit most from additional treatment support (e.g., reading and writing support). Helping participants to fully complete the Tai Aroha programme will provide them and their whānau with the essential skills and reintegration support. The simple rule we developed is consistent with the wider Hōkai Rangi strategy that Ara Poutama Aotearoa is implementing to increase positive outcomes for Māori in their care. Almost all the men entering Tai Aroha identify as Māori, and increasing the likelihood that they will complete treatment is a crucial step in Ara Poutama Aotearoa's plan to address the over-representation of Māori in the correctional system (Ara Poutama Aotearoa, 2019).

Practically, we have no control over the way staff may use the simple rule we have developed. A model, such as the one we have developed, is designed to alert staff to those who are better suited for treatment and those who need extra support to succeed. The rule is a measure of completion prediction, not a measure of treatability. Our simple rule will provide an additional source of information among many that Tai Aroha staff can consider when making assessments about whether referred men are likely to complete without additional responsivity support, or if they are at a higher risk of not completing and may require extra attention and support. We will inform staff of how and when the rule should be used during their selection processes, but we are unable to ensure how staff will use this rule practically.

Limitations

Our study had several limitations. The sample used for this research presented several problems. First, our sample size was limited ($N = 258$). Having 258 participants means our sample was very small for the development of an actuarial tool (Hanson, 2022). Second, the sample included all those who have entered Tai Aroha since the programme began in 2010, which makes some of the data over 10 years old at the time of analysis. The period of the data could also have caused a cohort effect, where characteristics of a group vary over time due to their different developmental experiences. This cohort effect may limit the generalisability of our findings because of the uniqueness of the sample.

The simple rule was developed specifically for Tai Aroha staff on a specific type of sample (i.e., high-risk violent men on community sentences) so assessing the rule on a more diverse sample may lead to the rule performing poorly. Confirming the result of this study on a new Tai Aroha sample may, however, also result in poor test performance. Our cross-validation results showed the unreliability of the model with a kappa score of 0.25, which is considered ‘minimal’ or less than 15% reliable by Landis and Koch (1977). This score shows replications of the results from this study with a new Tai Aroha sample is unlikely because of how poorly the model would perform on further testing. Further testing to understand the reliability of the tool should therefore be considered before implementation.

Finally, another limitation is the nature of the variables we had available to develop our simple rule from. The variables we had were historical records captured for each participant in the five years before starting Tai Aroha, which meant some alerts, misconduct charges, and incidents may have occurred over four years before starting treatment. The variables we used in our analysis were all binary and were recoded from continuous variables for simplicity. This recoding may have resulted in a loss of valuable information, where a participant with 20 misconduct charges is put in the same category as a participant with one charge. The simplicity and quantitative nature of the variables in our rule do not consider the complexities of the participants, their motivations for treatment, or any other extraneous circumstances (e.g., location of the programme) that may need to be considered when participants are selected for treatment.

Future Research

Future research could look at the further application of simple rules for offender treatment programmes. Our simple rule may not be suited to aid staff decision-making at other treatment programmes other than Tai Aroha (because of the specificity of our sample), but the idea and method can be applied more widely. Having one rule would be useful across all correctional programmes, however, we acknowledge this may be impossible due to the different participants' programmes target. Applying the method and ideas of this research to develop different simple rules for treatment programmes could be effective in helping to increase treatment completion across offender treatment programmes.

Future research may be beneficial to investigate real-world cases and the comparison of the simple rule against unaided decisions. Comparing aided and unaided decisions by Tai Aroha service assessors or staff selecting participants using our simple rule may be able to determine not only if the tool is helping to increase treatment completion, but also further the soundness of using decision support tools in the context of selecting participants for treatment. Further research into the allocation of resources for those identified as having a higher risk of not completing treatment may also help to reduce the cost of treatment attrition.

Conclusion

Offender attrition remains a serious ongoing problem for treatment programmes. In this work, we were successful in identifying predictors of treatment completion vs. non-completion and in the development of a simple rule to guide staff decisions at Tai Aroha. Our research expands our understanding of the rates of treatment completion among high-risk violent offenders engaging in community-based treatment and factors that predict treatment completion vs. non-completion. The results of this study have confirmed past results that older age and a lack of mental health concerns, institutional misconducts, and incidents can predict treatment completion (Dowden & Serin, 2001; Kroner et al., 2014; Nunes et al., 2010). For our second aim, we developed two simple rules, one rule with two variables and one with three variables and outlined the advantages and disadvantages of each. Model 2 is the most beneficial rule to use when making selection decisions, as it is less likely to result in completers missing out on treatment and will avoid the use of unnecessary resources. Staff can use our simple rule to identify Tai Aroha participants at a higher risk of not completing, to offer them additional resources that have the potential to increase treatment completion at Tai Aroha.

References

Ara Poutama Aotearoa. (2019). *Hōkai Rangi*. https://www.corrections.govt.nz/__data/assets/pdf_file/0003/38244/Hokai_Rangi_Strategy.pdf

Australian Bureau of Statistics. (2011). *Australian and New Zealand Standard Offence Classification (ANZSOC).* https://www.abs.gov.au/statistics/classifications/australian-and-new-zealand-standard-offence-classification-anzsoc/latest-release

Beyko, M. J., & Wong, S. C. P. (2005). Predictors of treatment attrition as indicators for program improvement not offender shortcomings: A study of sex offender treatment attrition. *Sexual Abuse*, *17*(4), 375–389. https://doi.org/10.1177/107906320501700403

Block, C. (2008). Rural-urban residency, treatment motivation, and health status as factors related to dropout from correctional substance abuse treatment: A policy perspective (Publication No. 3308359). [Doctoral dissertation, University of Louisville]. ProQuest One Academic.

Bonta, J. (2002). Offender risk assessment: Guidelines for selection and use. *Criminal Justice and Behavior, 29*(4), 355-379. https://doi.org/10.1177/0093854802029004002

Bonta, J., & Andrews, D. A. (2007). *Risk-need-responsivity model for offender assessment and rehabilitation*. Public Safety Canada. https://www.publicsafety.gc.ca/cnt/rsrcs/pblctns/rsk-nd-rspnsvty/index-en.aspx

Browne, K. D., Foreman, L., & Middleton, D. (1998). Predicting treatment drop-out in sex offenders. *Child Abuse Review (Chichester, England: 1992)*, *7*(6), 402–419. https://doi.org/10.1002/(SICI)1099-0852(199811/12)7:6<402::AID-CAR530>3.0.CO;2-9

Brownlee, J. (2023). *A Gentle Introduction to K-fold Cross-Validation*. Machine Learning Mastery. https://machinelearningmastery.com/k-fold-cross-validation/

Brunner, F., Neumann, I., Yoon, D., Rettenberger, M., Stück, E., & Briken, P. (2019). Determinants of dropout from correctional offender treatment. *Frontiers in Psychiatry*, *10*, 142–142. https://doi.org/10.3389/fpsyt.2019.00142

Carl, L. C., Schmucker, M., & Lösel, F. (2020). Predicting attrition and engagement in the treatment of young offenders. *International Journal of Offender Therapy and Comparative Criminology*, *64*(4), 355–374. https://doi.org/10.1177/0306624X19877593

Chakrabarti, A., & Ghosh, J. K. (2011). AIC, BIC and recent advances in model selection. In *Philosophy of Statistics*, (pp. 583–605). Elsevier B.V. https://doi.org/10.1016/B978-0-444-51862-0.50018-6

Craissati, J., & Beech, A. (2001). Attrition in a community treatment program for child sexual abusers. *Journal of Interpersonal Violence*, *16*(3), 205–221. https://doi.org/10.1177/088626001016003002

Cunha, O., Silva, A., Cruz, A. R., de Castro Rodrigues, A., Braga, T., & Gonçalves, R. A. (2023). Dropout among perpetrators of intimate partner violence attending an intervention program. *Psychology, Crime & Law*, *29*(6), 634–652. https://doi.org/10.1080/1068316X.2022.2030337

Daly, J. E., & Pelowski, S. (2000). Predictors of dropout among men who batter: A review of studies with implications for research and practice. *Violence and Victims*, *15*(2), 137–160. https://doi.org/10.1891/0886-6708.15.2.137

Department of Corrections. (2023). *Prison facts and statistics*. https://www.corrections.govt.nz/resources/statistics/quarterly_prison_statistics/prison_stats_march_2023

Dowden, C., & Serin, R. (2001). *Anger management programming for offenders: The impact of program performance measures*. https://publications.gc.ca/collections/collection_2010/scc-csc/PS83-3-106-eng.pdf

Drapeau, M., Körner, A., Granger, L., Brunet, L., & Caspar, F. (2005). A plan analysis of pedophile sexual abusers' motivations for treatment: A qualitative pilot study. *International Journal of Offender Therapy and Comparative Criminology*, *49*(3), 308–324. https://doi.org/10.1177/0306624X04272853

Edwards, R., Beech, A., Bishopp, D., Erikson, M., Friendship, C., & Charlesworth, L. (2007). Predicting dropout from a residential programme for adolescent sexual abusers using pre-treatment variables and implications for recidivism. *The Journal of Sexual Aggression*, *11*(2), 139–155. https://doi.org/10.1080/13552600500063641

Elonheimo, H., Gyllenberg, D., Huttunen, J., Ristkari, T., Sillanmäki, L., & Sourander, A. (2014). Criminal offending among males and females between ages 15 and 30 in a population-based nationwide 1981 birth cohort: Results from the FinnCrime Study. *Journal of Adolescence (London, England)*, *37*(8), 1269–1279. https://doi.org/10.1016/j.adolescence.2014.09.005

Penal Reform International. (2022). *Ethnic minorities and indigenous peoples*. https://www.penalreform.org/global-prison-trends-2022/ethnic-minorities/

Garner, B. R., Knight, K., & Simpson, D. D. (2007). Burnout among corrections-based drug treatment staff: Impact of individual and organizational factors. *International Journal of*

Offender Therapy and Comparative Criminology, *51*(5), 510–522. https://doi.org/10.1177/0306624X06298708

Geer, T. M., Becker, J. V., Gray, S. R., & Krauss, D. (2001). Predictors of treatment completion in a correctional sex offender treatment program. *International Journal of Offender Therapy and Comparative Criminology*, *45*(3), 302–313. https://doi.org/10.1177/0306624X01453003

Hanson, R. K. (2022). *Estimating the quality of prediction tools.* In Prediction statistics for psychological assessment (pp. 325-352). American Psychological Association. https://doi.org/10.1037/0000275-017

Hanson, R. K. (2022). *Dichotomous Predictors.* In Prediction statistics for psychological assessment (pp. 103-133). American Psychological Association. https://doi.org/10.1037/0000275-007

Helmus, L. M., & Babchishin, K. M. (2017). Primer on risk assessment and the statistics used to evaluate its accuracy. *Criminal Justice and Behavior*, *44*(1), 8–25. https://doi.org/10.1177/0093854816678898

Howard, M. V. A., de Almeida Neto, A. C., & Galouzis, J. J. (2019). Relationships between treatment delivery, program attrition, and reoffending outcomes in an intensive custodial sex offender program. *Sexual Abuse, 31*(4), 477–499. https://doi.org/10.1177/1079063218764886

Howells, K., & Day, A. (2007). Readiness for treatment in high risk offenders with personality disorders. *Psychology, Crime and Law, 13*(1), 47–56. https://doi.org/10.1080/10683160600869767

James, G., Witten, D., Hastie, T., & Tibshirani R. (2013) *An introduction to statistical learning: With applications in R*, (pp. 181-202). Springer.

Jeandarme, I., Habets, P., O'Reilly, K., & Kennedy, H. G. (2021). Is non-completion of treatment related to security need? *Criminal Behaviour and Mental Health*, *31*(5), 321–330. https://doi.org/10.1002/cbm.2213

Jewell, L. M., & Wormith, J. S. (2010). Variables associated with attrition from domestic violence treatment programs targeting male batterers: A meta-analysis. *Criminal Justice and Behavior*, *37*(10), 1086–1113. https://doi.org/10.1177/0093854810376815

Jung, J., Concannon, C., Shroff, R., Goel, S., & Goldstein, D. G. (2020). Simple rules to guide expert classifications. *Journal of the Royal Statistical Society: Series A, Statistics in Society*, *183*(3), 771–800. https://doi.org/10.1111/RSSA.12576

Kahneman, D., Sibony, O., & Sunstein, C. (2021). Noise: A Flaw in Human Judgment. William Collins.

Kilgour, G. (2015). *Tai Aroha Evaluation Project Report*. Department of Corrections. https://www.corrections.govt.nz/__data/assets/pdf_file/0008/42785/Tai_Aroha_Evaluation_Project_Report_2015.pdf

King, L. (2012). *Tai Aroha - The first two years: A formative evaluation of a residential community based programme for offenders*. Department of Corrections. https://www.corrections.govt.nz/__data/assets/pdf_file/0017/10772/COR_Tai_Aroha_WEB.pdf

Konecky, B., Cellucci, T., & Mochrie, K. (2016). Predictors of program failure in a juvenile drug court program. *Addictive Behaviors, 59*, 80–83. https://doi.org/10.1016/j.addbeh.2016.03.025

Kopak, A. M., Dean, L. V., Proctor, S. L., Miller, L., & Hoffmann, N. G. (2015). Effectiveness of the rehabilitation for addicted prisoners trust (RAPt) programme. *Journal of Substance Use*, *20*(4), 254–261. https://doi.org/10.3109/14659891.2014.904938

Kraemer, B. D., Salisbury, S. B., & Spielman, C. R. (1998). Pretreatment variables associated with treatment failure in a residential juvenile sex-offender program. *Criminal Justice and Behavior*, *25*(2), 190–203. https://doi.org/10.1177/0093854898025002003

Kroner, D. G., Power, J., Takahashi, M., & Harris, A. J. R. (2014). Predicting treatment attrition among seriously violent offenders: An application of the directionality model. *Journal of Interpersonal Violence*, *29*(12), 2239–2256. https://doi.org/10.1177/0886260513517551/FORMAT/EPUB

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159. https://doi.org/10.2307/2529310

Loeb, R. C., Waung, M., & Sheeran, M. (2015). Individual and familial variables for predicting successful completion of a juvenile justice diversion program. *Journal of Offender Rehabilitation, 54*(3), 212–237. https://doi.org/10.1080/10509674.2015.1023482

McMurran, M., & Theodosi, E. (2007). Is treatment non-completion associated with increased reconviction over no treatment? *Psychology, Crime & Law, 13*(4), 333–343. https://doi.org/10.1080/10683160601060374

Monaghan, T. F., Rahman, S. N., Agudelo, C. W., Wein, A. J., Lazar, J. M., Everaert, K., & Dmochowski, R. R. (2021). Foundational statistical principles in medical research: sensitivity, specificity, positive predictive value, and negative predictive value. *Medicina (Kaunas, Lithuania), 57*(5), 503-. https://doi.org/10.3390/medicina57050503

Mossière, A., & Serin, R. (2014). A critique of models and measures of treatment readiness in offenders. *Aggression and Violent Behavior*, *19*(4), 383–389. https://doi.org/10.1016/J.AVB.2014.06.004

Muriwai, E., Houkamau, C. A., Sibley, C. G., Muriwai, E., Houkamau, C. A., & Sibley, C. G. (2015). Culture as Cure? The Protective Function of Māori Cultural Efficacy on Psychological Distress. *New Zealand Journal of Psychology (Christchurch. 1983), 44*(2), 14–24.

Nicholls, T. L., Pritchard, M. M., Reeves, K. A., & Hilterman, E. (2013). Risk assessment in intimate partner violence: A systematic review of contemporary approaches. *Partner Abuse*, *4*(1), 76–168. https://doi.org/10.1891/1946-6560.4.1.76

Nunes, K. L., & Cortoni, F. (2006). *Estimating Risk of Dropout and Expulsion from Correctional Programs*. Correctional Service of Canada.

Nunes, K. L., Cortoni, F., & Serin, R. C. (2010). Screening offenders for risk of drop-out and expulsion from correctional programmes. *Legal and Criminological Psychology*, *15*(2), 341–356. https://doi.org/10.1348/135532508X401887

Olver, M. E., Stockdale, K. C., & Wormith, J. S. (2011). A meta-analysis of predictors of offender treatment attrition and its relationship to recidivism. *Journal of Consulting and Clinical Psychology*, *79*(1), 6. https://doi.org/10.1037/A0022200

Parikh, R., Mathai, A., Parikh, S., Chandra Sekhar, & Thomas, R. (2008). Understanding and using sensitivity, specificity and predictive values. *Indian Journal of Ophthalmology, 56*(1), 45–50. https://doi.org/10.4103/0301-4738.37595

Polaschek, D. L. L. (2010). Treatment non-completion in high-risk violent offenders: looking beyond criminal risk and criminogenic needs. *Psychology, Crime & Law, 16*(6), 525–540. https://doi.org/10.1080/10683160902971048

Polaschek, D. L. L., & Dixon, B. G. (2008). The violence prevention project: The development and evaluation of a treatment programme for violent offenders. *Psychology, Crime & Law, 7*(1), 1–23. https://doi.org/10.1080/10683160108401779

Robinson, K. D., & Little, G. L. (1982). One-day dropouts from correctional drug treatment. *Psychological Reports, 51*(2), 409-410. https://doi.org/10.2466/pr0.1982.51.2.409

Ryan, R. M., Plant, R. W., & O'Malley, S. (1995). Initial motivations for alcohol treatment: Relations with patient characteristics, treatment involvement, and dropout. *Addictive Behaviors*, *20*(3), 279–297. https://doi.org/10.1016/0306-4603(94)00072-7

Serin, R. (1998). *Treatment responsivity, intervention, and reintegration: A conceptual model.* Correctional Service Canada. https://www.csc-scc.gc.ca/research/forum/e101/e101f-eng.shtml

Skeem, J. L., Polaschek, D. L. L., & Manchak, S. (2009). Appropriate treatment works, but how?: Rehabilitating general, psychopathic, and high-risk offenders. In J. L. Skeem (Ed.) & K. S. Douglas & S. O. Lilienfeld (Ed.), *Psychological science in the courtroom: Consensus and controversy* (pp. 358–384). The Guilford Press. https://psycnet.apa.org/record/2009-11373-016

Steketee, G., & Chambless, D. L. (1992). Methodological issues in prediction of treatment outcome. *Clinical Psychology Review*, *12*(4), 387–400. https://doi.org/10.1016/0272-7358(92)90123-P

Stokes, H., Dixon, L., & Beech, A. (2009). Predicting drop out of incarcerated men from a long-term aggression programme. *Journal of Aggression, Conflict and Peace Research, 1*(1), 36–44. https://doi.org/10.1108/17596599200900005

Stoltzfus, J. C. (2011). Logistic regression: A brief primer. *Academic Emergency Medicine, 18*(10), 1099–1104. https://doi.org/10.1111/j.1553-2712.2011.01185.x

Wertz, M., Schobel, S., Schiltz, K., & Rettenberger, M. (2023). A comparison of the predictive accuracy of structured and unstructured risk assessment methods for the prediction of recidivism in individuals convicted of sexual and violent offense. *Psychological Assessment*, *35*(2), 152. https://doi.org/10.1037/PAS0001192

Wooditch, A., Larry Tang, L., & Taxman, F. S. (2014). Which criminogenic need changes are most important in promoting desistance from crime and substance use? *Criminal Justice and Behavior, 41*(3), 276–299. https://doi.org/10.1177/0093854813503543

Wormith, J. S., & Olver, M. E. (2002). Offender treatment attrition and its relationship with risk, responsivity, and recidivism. *Criminal Justice and Behavior*, *29*(4), 447–471. https://doi.org/10.1177/0093854802029004006

Zane, S. N., Pupo, J. A., & Welsh, B. C. (2023). Correctional treatment as an economically sound approach to reducing the high costs of recidivism: A review of the research. *Criminal Behaviour and Mental Health*, *33*(2), 125–138. https://doi.org/10.1002/CBM.2284

Zhang, Z. (2016). Variable selection with stepwise and best subset approaches. *Annals of Translational Medicine*, *4*(7), 136-136. https://doi.org/10.21037/ATM.2016.03.35

Appendix A

Table 9

Full List of Variables from Data Supplied by Ara Poutama Aotearoa: Including description and Example.

Variable name	Description	Example
Demographic variables		
Offender ID	Unique identifier for each participant	00M567NZ
Age	Age at the commencement of sentence	30
RoC*RoI score	Statistical assessment of the likelihood of reoffending and reimprisonment within five years.	0.81
Gang affiliation	Whether the offender is associated with a gang or not*	
Prison/sentence related variables		
Directive type	Type of sentence/order active	Violent
Directive start date	Start date of sentence	8/08/11
Directive end date	End date of sentence	23/11/11
Lead offence	Offence that imposes the most severe penalty	Violent
Lead offence description	Detail of lead offence	Assault
Lead sexual offence	Whether the lead offence was a sex offence*	
Lead child sex offence	Whether the lead offence was a child sex offence*	
Lead family harm offence	Whether the lead offence was a family harm offence*	
Aggregate sex offence	If there is any other active sex offence during the same sentence*	
Aggregate child sex offence	If there is any other active child sex offence during the same sentence*	

Aggregate violent offence	If there is any other active violent offence during the same sentence*	
Aggregate family harm offence	If there is any other active family harm offence during the same sentence*	
Ever sexual sentence	If the offender has ever been sentenced for a sex offence*	
Ever child sex sentence	If the offender has ever been sentenced for a child sex offence*	
Ever family harm sentence	If the offender has ever been sentenced for a family harm offence*	
Number of previous community sentence	Count of all previous community-based sentences	
Number of previous custodial sentence	Count of all previous custodial sentences	
Number of days spent on remand	Number of days spent in remand custody in the past five years	
Number of days spent as a sentenced prisoner	Number of days spent as a sentenced prisoner in the past five years	
Programme variables		
Start date	Start date of Tai Aroha	11/11/15
End date	The end date of Tai Aroha	02/04/16
Start indicator	Indication of treatment start*	
Completed indicator	Indication of treatment completion*	
Exit indicator	Indication of treatment exist*	
Exit Reason	Reason for existing the programme for non-completers	Poor responsivity
Misconduct variables		
Misconduct count	Number of misconduct charges in 5 years before Tai Aroha start date	

Misconduct charge	A description of the misconduct charge. See Table 12 for a full list of charges	
Incident variables		
Incident ID	Unique identifier for each incident	
Incident event date time	Date of incident	
Participant role	Participants role in the incident	Victim
Incident primary category	The primary category of the incident	Prison behaviour
Incident secondary category	The secondary category of the incident	Wilful damage
Incident tertiary category	Tertiary category of the incident	Break prison rules
Incident count	Number of incidents the participant has been involved in, in the 5 years before Tai Aroha start date	
Alerts		
Offender alert type	Type of alerts active in the five years	Gang Affiliation
Alert count	Number of alerts active in the 5 years before Tai Aroha start date	

Note. All variables were captured at the time of Tai Aroha start. * = dichotomous variable (1= yes, 0 =no).

Table 10

Australia and New Zealand Standard Offence Classification (ANZSOC) Variables

Variable name	Example
1. Abduction, harassment, and other offences against the person	Kidnapping, harassment
2. Acts intended to cause injury	Inflict injury with no intent to kill
3. Dangerous or negligent acts endangering persons	Dangerous operation of a vehicle
4. Fraud, deception, and related offences	Forgery and counterfeiting

5. Illicit drug offences	Import or export of illicit drugs
6. Miscellaneous offences	Defamation, privacy offences
7. Offences against justice procedures, government security, and government operations	Breach of community-based order
8. Prohibited and regulated weapons and explosives offences	Possession of weapons/explosives
9. Property damage and environmental pollution	Arson, pollution, animal cruelty
10. Public order offences	Disorderly conduct
11. Robbery, extortion, and related offences	Blackmail, extortion
12. Theft and related offences	Motor vehicle theft
13. Traffic and vehicle regulatory offences	Driver licence offences
14. Unlawful entry with intent/burglary, break and enter	Ram raid, smash and grab

Note. The above 15 variables involve the count of previous convictions based on the ANZSOC offence grouping system. This grouping system, developed in 2008, classifies criminal behaviour into a uniform national statistical framework (Australian and New Zealand Standard Offence Classification (2001). ANZSOC variables used in this study are based on ANZSOC 2011 release.

ANZSOC report: https://www.abs.gov.au/statistics/classifications/australian-and-new-zealand-standard-offence-classification-anzsoc/2011

Table 11

List of Incidents

Variable name	Example
Contraband/exhibits	Cell phone, tobacco, tattooing device
Facilities	The event was in a shared cell
Other	Any other event not requiring official notification

Prison security	Breach of security
Prisoner behaviour	Fighting, prisoner verbally abuses/threatens staff
Prisoner management	Handcuffs, receives bad news, threatens self-harm
Prisoner safety/ welfare	Self-harm – no threat to life, illness
Visitor incident	Visitor acts inappropriately with prisoner, visitor refused entry

Table 12

List of Misconduct Charges

Variable name	Description	Corrections acts, subsection
Disobeys lawful order	Disobeys any lawful order of an officer or a staff member, or disobeys or fails to comply with any regulation made under Corrections Act 2004 Section 128.	128, 1, a
Intentionally mismanages	Intentionally mismanages work.	128, 1, b
Behaves offensively	Behaves in an offensive, threatening, abusive, or intimidating manner.	128, 1, c
Without authority	Without authority, communicates with any person inside or outside the prison by using a telephone or other electronic communication device.	128, 1, d
Leaves cell	Leaves or is absent from his or her cell or place of work or other place where the prisoner is required to be without permission or reasonable excuse.	128, 1, e
Without approval	Without the approval of an officer, has any article in his or her cell or in his or	128, 1, f

	her possession, or gives to or receives from any person any article, or attempts to obtain any article.	
Assault or fights	Assaults, or fights with, any other person.	128, 1, g
Deliberately disfigures	Deliberately disfigures, damages, or destroys any part of the prison or any property that is not his or her own, or who loses any prison property because of his or her negligence or improper conduct.	128, 1, h
Obstructs officer	Obstructs any officer in the execution of his or her duty.	128, 1, i
Endanger good order	Combines with other prisoners for a purpose that is likely to endanger the security or good order of the prison.	128, 1, k
Without medical officer	Without the authority of a medical officer or health centre manager or unless section 79(3) applies, uses any drug or consumes alcohol (whether inside or outside a prison).	129, a
Smokes	Smokes tobacco or any other substance, or vapes within the meaning of section 2 of the Smokefree Environments and Regulated Products Act 1990, inside a prison.	129, aa
Refuses to comply	Having been required under section 124 to submit to a prescribed procedure, refuses to comply with the requirement.	129, b, i
Fails to comply	Having been required under section 124 to submit to a prescribed procedure,	129, b, ii

	without reasonable excuse, fails to comply with the requirement

Note. The schedule of misconduct offences can be found:

https://www.corrections.govt.nz/resources/policy_and_legislation/Prison-Operations-Manual/Public-RL/MC.01.Sch.01-Schedule-of-offences

Table 13

List of Alert Types

Variable	Descriptions/ Example
Aggression	Prisoner is prone to being aggression towards staff
Alcohol problems	Prisoner has problems with alcohol use
Assault domestic	History of domestic assault
Assault to staff - history of	History of assault towards staff
At risk	Prison alert
At risk from others	Prisoner alert
Blind	Offender is blind
Child protection policy	Subject to information sharing agreement relating to child sex offenders
Classification	Note re-security classification
Covid-19 - vulnerable	Vulnerable person with regards to COVID-19
Covid-19 quarantine - confirmed - positive	Confirmed/positive test of Covid-19
Covid-19 quarantine - probable or suspected symptoms	Suspected/probable symptoms related to Covid-19
Covid-19 separation	Separated due to positive Covid-19 test
Cpps high risk offender	Community Probation and Psychological Service group warning for high risk
Cso info sharing agreement	Subject to the information sharing agreement relating to child sex offenders

Cumulative community based sentence	Community sentence to follow imprisonment
Driving disqualification	Driving while disqualified
Drugs	Alert for drugs
Forensic concerns	Contact with a forensic mental health service
Gang affiliation	Prisoner affiliated with a gang
Health	General health alert
Hearing problems	General hearing problems alert
Home visit health & safety	Flag for higher risk home visits
Intelligence held	Intelligence sector holds information on the prisoner that should not be available in their file
Ipa status 1	Identified abuser of the prison phone system
Non-association	Flag to identify other prisoners this person should not be placed with, or visitors who are prohibited.
Ntdb	Not to double bunk
Outstanding breach	Outstanding breach of sentence
Outstanding recall	Outstanding parole recall
Outstanding review	Outstanding breach of sentence
Overseas conviction	Has had an overseas conviction
Placement review filed	Flag that prisoner has requested change of unit placement
Placement review granted	Flag that unit placement has been granted, with reasons and data to ensure regime isn't changed
Protection order	Flag for an active protection order
Racially motivated concerns	Flag for racially motivated person
Release	Alert related to release
Remand no contact condition	All contact with person specified in the condition is prohibited
Request for no contact	Prisoner has requested no contact form outside of prison

Risk of escape	Prison is/has been at risk of attempting to or succeeding escape
Risk of self-harm	Prison is/has been at risk of self-harm
Risk of suicide	Prison is/has been at risk of suicide
Seg58 1A directed security good order	Prisoner separated because security or good order of the prison would otherwise be endangered or prejudiced
Seg58 1B directed safety of others	The safety of another prisoner or person would otherwise be endangered.
Seg59 1A voluntary prisoner safety	The prisoner requests that his or her opportunity to associate be restricted or denied and the prison director considers, having regard to any information supplied by the prisoner or otherwise available to the prison director, that it is in the best interests of the prisoner to give that direction
Seg59 1B directed prisoner safety	He / she is satisfied that the safety of the prisoner has been put at risk by another person and there is no reasonable way to ensure the safety of the prisoner otherwise than by giving the direction.
Seg60 1A directed physical health	The health centre manager of the prison recommends the segregation to assess or ensure the prisoner's physical health excluding risk of self-harm
Seg60 1B directed mental health	The health centre manager of the prison recommends the segregation in order to assess or ensure the prisoner's mental health
Segregated	Prisoner is separated from prison population
Segregated section 58	Separated for purposes of security, good order or safety

Segregated section 59	Separated for purpose of protective custody.
Segregated section 60	Separated for medical oversight
Segregation request denied	Request for separation was denied
Tbi-R completed	Traumatic brain injury assessment
Threat to others	Prisoner is a physical threat to others
Transport	Flag for requirements during transport (e.g., not to be placed with another prisoner; claustrophobia)
Under 20	Prisoner is under 20 years of age
Victim family violence	Prison is/has been a victim of family harm
Vulnerable young adult	Unit placement needs special consideration, possible for placement in youth unit
Weapon	Prison is/has been at risk of using a weapon
Young person	Prisoner is under the age of 16

Appendix B

Table 14

Chi-square Test Comparing Sentence Variables and Completion Status

Variable		Completer		Non-completer				
	Total	*n*	%	*n*	%	X^2	*p*	*df*
Gang affiliation	140	80	50.3	60	60.6	2.60	.107	1
Lead offence family harm	134	85	53.5	49	51.6	0.08	.771	1
Aggregate violent offence	187	116	73.0	71	71.1	0.04	.828	1
Aggregate family harm offence	162	102	64.2	60	63.2	0.02	.873	1
Ever family harm sentence	222	139	87.4	83	87.4	0	.99	1

Note. N = 258 (completers = 159, non-completers = 99).

Table 15

Chi-square Test Comparing Occurrence of Alert Type and Completion Status

Variable		Completer		Non-completer				
	Total	*n*	%	*n*	%	X^2	*p*	*df*
Aggression	38	20	12.6	18	18.2	1.52	.217	1
Alcohol problems	5	3	1.9	2	2.0	0.01	.94	1
Assault domestic	76	42	26.4	34	34.3	1.85	.174	1
Assault to staff - history of	61	33	20.8	28	28.3	1.91	.166	1
At risk	34	16	10.1	18	18.2	3.51	.061	1
At risk from others	14	9	5.7	5	5.1	0.04	.833	1
Blind	1	0	0.0	1	1.0	1.61	.204	1
Child protection policy	24	15	9.4	9	9.1	0.01	.926	1
Classification	9	5	3.1	4	4.0	0.14	.703	1
Covid-19 - vulnerable	1	1	0.6	0	0.0	0.62	.429	1
Covid-19 quarantine – positive	3	2	1.2	1	1.0	0.03	.857	1
Covid-19 quarantine – suspected	4	3	1.9	1	1.0	0.31	.579	1

Covid-19 separation	27	14	8.8	13	13.1	1.22	.27	1
Cpps high risk offender	18	9	5.7	9	9.1	1.11	.293	1
Cso info sharing agreement	1	1	0.6	0	0.0	0.62	.429	1
Cumulative community sentence	3	3	1.9	0	0.0	1.90	.169	1
Driving disqualification	1	1	0.6	0	0.0	0.62	.429	1
Drugs	66	39	24.5	27	27.3	0.24	.623	1
Forensic concerns	18	6	3.8	12	12.1	6.55	**.01**	1
Gang affiliation	27	14	8.8	13	13.1	1.22	.27	1
Health	231	143	89.9	88	88.9	0.07	.789	1
Hearing problems	1	1	0.6	0	0.0	0.62	.429	1
Home visit health & safety	2	1	0.6	1	1.0	0.11	.734	1
Intelligence held	27	17	10.7	10	10.1	0.02	.88	1
Ipa status 1	4	2	1.3	2	2.0	0.23	.63	1
Non-association	140	86	54.1	54	54.5	0.01	.943	1
Ntdb	8	5	3.1	3	3.0	0.01	.959	1
Outstanding breach	4	2	1.3	2	2.0	0.23	.63	1
Outstanding recall	1	0	0.0	1	1.0	1.61	.204	1
Outstanding review	1	1	0.6	0	0.0	0.62	.429	1
Overseas conviction	1	0	0.0	1	1.0	1.61	.204	1
Placement review filed	1	0	0.0	1	1.0	1.61	.204	1
Placement review granted	4	3	1.6	1	1.0	0.31	.579	1
Protection order	90	60	37.7	30	30.3	1.48	.223	1
Racially motivated concerns	1	0	0.0	1	1.0	1.61	.204	1
Release	11	7	4.4	4	4.0	0.02	.889	1
Remand no contact condition	22	14	8.8	8	8.1	0.04	.839	1
Request for no contact	7	3	1.9	4	4.0	1.07	.30	1
Risk of escape	53	30	18.9	23	23.2	0.71	.399	1
Risk of self-harm	134	69	43.4	65	65.7	12.11	**<.001**	1
Risk of suicide	57	32	20.1	25	25.3	0.93	.334	1
Seg58 1A directed security good order	45	21	13.2	24	24.2	4.16	**.023**	1

Seg58 1B directed safety of others	30	15	9.4	15	15.2	1.94	.164	1
Seg59 1A voluntary prisoner safety	155	93	58.5	62	62.6	0.43	.51	1
Seg59 1B directed prisoner safety	11	5	3.1	6	6.1	1.27	.26	1
Seg60 1A directed physical health	8	5	3.1	3	3.0	0.01	.959	1
Seg60 1B directed mental health	3	0	0.0	3	3.0	4.87	**.027**	1
Segregated	15	3	1.9	12	12.1	11.67	**<.001**	1
Segregated section 58	9	2	1.3	7	7.1	6.12	**.013**	1
Segregated section 59	44	24	15.1	20	20.2	1.12	.289	1
Segregated section 60	1	0	0.0	1	1.0	1.61	.204	1
Segregation request denied	24	14	8.8	10	10.1	0.12	.727	1
TBI-R completed	5	1	0.6	4	4.0	3.74	.053	1
Threat to others	27	13	8.2	14	14.1	2.31	.128	1
Transport	7	1	0.6	6	6.1	6.82	**.009**	1
Under 20	50	21	13.2	29	29.3	10.10	**.001**	1
Victim family violence	4	2	1.3	2	2.0	0.23	.63	1
Vulnerable young adult	9	3	1.9	6	6.1	3.16	.076	1
Weapon	68	49	30.8	19	19.2	4.25	**.039**	1
Young person	9	2	1.3	7	7.1	6.12	**.013**	1

Note. N = 258 (completers = 159, non-completers = 99).

Table 16

Chi-square Test Comparing Misconduct Charges and Completion Status

Variable		Completer		Non-completer				
	Total	***n***	**%**	***n***	**%**	**X^2**	***p***	***df***
Assaults, or fights	70	30	18.9	40	40.4	14.31	**<.001**	1
Behaves offensively	53	24	15.7	28	28.3	5.89	**.015**	1
Endanger good order	4	1	0.6	3	3.0	2.30	.129	1
Deliberately disfigures	45	18	11.3	27	27.3	10.78	**<.001**	1

Disobeys any lawful order	90	48	30.2	42	42.4	4.02	**.045**	1
Refuses to comply	4	2	1.3	2	2.0	0.23	.63	1
Fails to comply	1	0	0.0	1	1.0	1.61	.204	1
Leaves cell	2	1	0.6	1	1.0	0.11	.734	1
Obstructs any officer	5	0	0.0	5	5.1	8.18	**.004**	1
Smokes	11	8	5.0	3	3.0	0.60	.439	1
Without authority	4	2	1.3	2	2.0	0.23	.63	1
Without the approval	124	75	47.2	49	49.5	0.13	.716	1
Without medical officer	27	16	10.1	11.1	0.1	0.07	.789	

Note: $N = 258$ (completers = 159, non-completers = 99).

Table 17

Chi-square Test Comparing ANZSOC Category and Completion Status

Variable		**Completer**		**Non-completer**				
	Total	***n***	***%***	***n***	***%***	**X^2**	***p***	***df***
Abduction, harassment and other offences against the person	148	91	57.2	57	57.7	0.01	.957	1
Acts intended to cause injury	253	155	98	98	99	0.73	.394	1
Dangerous/negligent acts endangering persons	185	177	73.6	68	68.7	0.72	.396	1
Fraud, deception and related offences	93	57	35.8	36	36.4	0.01	.933	1
Illicit drug offences	192	123	77.4	69	69.7	1.88	.17	1
Miscellaneous offences	23	9	5.7	14	14.1	5.40	**.02**	1

Offences against justice procedures, government security and government operations	257	159	100	98	99	1.61	.204	1
Prohibited and regulated weapons and explosives offences	167	101	63.5	66	66.7	0.26	.607	1
Property damage/ environmental pollution	229	147	92.5	82	82.8	5.66	**.017**	1
Public order offences	230	146	91.8	84	84.8	3.07	.08	1
Robbery, extortion and related offences	104	63	39.6	41	41.4	0.08	.775	1
Theft and related offences	242	152	95.6	90	90.9	2.31	.129	1
Traffic and vehicle regulatory offences	234	148	93.1	86	86.9	2.79	.095	1
Unlawful entry with intent/burglary, break and enter	217	137	86.2	80	80.8	1.31	.253	1

Note. $N = 258$ (completers = 159, non-completers = 99).

Table 18

Chi-square Test Comparing Incident Categories and Completion Status

Variable		**Completer**		**Non-completer**				
	Total	***n***	**%**	***n***	**%**	**X^2**	***p***	***df***
Perpetrator	234	143	89.9	91	91.9	0.28	.594	1
Victim	159	84	52.8	75	75.8	13.56	**<.001**	1
Accomplice	57	30	18.9	27	27.3	2.50	.114	1
Witness	63	37	23.3	26	26.3	0.29	.586	1

Incident category								
Contraband/exhibits	169	102	64.2	67	67.7	0.34	.562	1
Facilities	120	67	42.1	53	53.5	3.18	.074	1
Other	58	29	18.2	29	29.3	4.27	**.039**	1
Prison security	80	47	27.6	33	33.3	0.41	.524	1
Prisoner behaviour	210	123	77.4	87	87.9	4.46	**.035**	1
Prisoner management	152	85	53.5	67	67.7	5.09	**.024**	1
Prisoner safety/welfare	67	32	20.1	35	35.4	7.36	**.007**	1
Visitor incident	5	2	1.3	3	3	1.01	.315	1

Note. $N = 258$ (completers = 159, non-completers = 99).