Classifying Justice-Involved Males in Iowa: A Latent Class Analysis with the Dynamic Risk Assessment for Offender Re-Entry (DRAOR)

by

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Abstract

Recently, person-centered approaches to risk assessment have begun to be explored to examine how risk, need, and strength factors are dispersed across heterogeneous, correctional populations. Latent class analysis offers the ability to group individuals based on their similar characteristics, providing information about how these factors operate together and relate to one's propensity of engaging in criminal behaviour. The goal of the present study was to examine the utility of a person-centered approach with the Dynamic Risk Assessment for Offender Re-entry (DRAOR). The sample consisted of 510 justice-involved males from the state of Iowa. Latent class analysis yielded five distinct classes: 1) a low dynamic risk/high protective class, 2) a moderate to high dynamic risk/moderate to high protective class, 3) a moderate dynamic risk/moderate protective class, 4) a problematic employment/insufficient social support class and 5) a low to moderate dynamic risk/moderate protective class. Additional analyses revealed differences amongst the classes related to static risk, age, race, and recidivism outcomes. Lastly, area under the curve (AUC) analysis demonstrated the limited utility of the latent classes when predicting recidivism, supporting the continued use of DRAOR total scores to predict outcome. Nonetheless, the resultant classes provide information to enhance case management practices by providing specified case-level treatment targets regarding intervention. Finally, limitations, implications, and directions for future research were considered.

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Classifying Justice-Involved Males in Iowa: A Latent Class Analysis with the Dynamic Risk Assessment for Offender Re-Entry (DRAOR)

Structured risk assessments play a key role in the development of a case management plan for individuals involved in the criminal justice system. These assessments provide an estimated level of risk, while also aiding in the identification of targets for intervention (Hanson, 2009). However, these assessments tend to operate under the assumption that risk factors affect everyone in the same manner, representing a linear approach (i.e., as risk factors increase so does the corresponding risk level). This neglects the reciprocal relationship between risk, need, and strength factors and how individuals may have varying degrees in each, leading to more integrated models of risk (Helfgott, 2008). Recently, person-centered approaches are being explored to examine how these factors operate together to create holistic profiles of risk and how these profiles influence criminality across the life-course (Brennan et al., 2012; Helfgott, 2008; Miller et al., 2009; Seto & Fernandez, 2011; Schwalbe et al., 2008). Person-centered approaches (e.g., finite mixture modeling) may complement traditional variable-centered approaches (e.g., regression) allowing for larger heterogeneous populations to be reduced into smaller, more manageable groups based on distributions of risk and need (Schwalbe et al., 2008).

Currently, the Iowa Department of Corrections is responsible for a total of 37, 464 justice-involved individuals. This includes 7, 573 currently incarcerated individuals and 29, 891 on community supervision (Iowa Department of Corrections, 2020). Of those on community release, 62% are on probation and 16% are on parole (Iowa Department of Corrections, 2020). Community-based corrections in Iowa have a success rate of 57% with a 38.8% return rate to prison (Iowa Department of Corrections, 2020). The average daily cost for an institutionalized individual is $74.66 compared to an average of $6.12 per day for those who are on parole or

probation (Iowa Department of Corrections, 2020). This large recidivism rate combined with the large discrepancy in fiscal costs associated with incarceration and community-based releases amplifies the importance of ensuring strategies to reduce offending are appropriate and effective. The Iowa Department of Corrections adheres to the Risk, Need, Responsivity (RNR; Bonta & Andrews, 2017) model for all intervention programs and utilizes empirically validated risk assessments to assess offending risk and impose appropriate supervision levels (IDOC, 2019). Specifically, anyone released to an area of community-based corrections is assessed on the Iowa Risk Assessment Revised (IRR; Formally the Iowa Risk Assessment; IRA[1]), an actuarial tool used to measure static risk. Those who are assigned a supervision of level three or higher are additionally assessed on the Dynamic Risk Assessment for Offender Re-entry (DRAOR; Serin, 2007; 2015; 2017). Sub-groups, uncovered through a person-centered approach, can be a crucial asset in ensuring individuals are placed in programming consistent with the RNR model. Hence, Iowa is an ideal site to examine the utility of a person-centered approach to risk assessment.

The DRAOR is a structured case management tool used with justice-involved adults to provide direction in terms of case management and intervention strategies. It is comprised of both dynamic risk and strength-based items (termed protective factors in the DRAOR). For research purposes, to assess the predictive utility of the instrument, a total score is generated (ranging from -12-26). Lower scores indicate a lower risk, while higher scores indicate a higher risk (Serin et al., 2020). While studies have demonstrated that DRAOR total scores are predictive of recidivism outcomes (see psychometric properties section), the focus on total scores may miss vital information provided by the variability in person-specific scores on each item. For example,

[1] The original Iowa Risk Assessment (IRA) will be used in the current study as this is the assessment tool that was in use at the time of data collection.

consider that the DRAOR includes 19 items, with scores ranging from -12-26. Total scores based on how an individual scores in each of these areas are utilized to determine risk and supervision level; individual item scores inform case planning. When assessing a sample of justice-involved individuals on this measure, a variable-centered analysis may indicate that, based on total scores, two different individuals are both high-risk and require a general high-intensity program. However, if you look at their individual scores, they may yield identical total scores but differ in their criminogenic needs (e.g., impulse control vs. peer associations) and thus require a more specialized intervention plan according to these specific patterns of criminogenic needs (Schwalbe et al., 2008).

The present study examined the utility of a person-centered approach in categorizing a sample of justice-involved males from Iowa into discrete classes based on dynamic risk and strength factors derived from the DRAOR. The resultant classes should enhance case management practices by providing specified treatment targets and informing intervention. Additionally, direction could be provided regarding the allocation of resources based on class size and the distribution of criminogenic needs (e.g., programming resources should match profile characteristics). Overall, there were three main areas of exploration: (1) to determine if meaningful classes can be elucidated from the dynamic and strength items (i.e., protective items) that comprise the DRAOR; (2) to determine if static risk scores and individual characteristics (e.g., age, race) are related to class membership; and (3) to assess the utility of the resultant classes in enhancing the prediction of recidivism outcomes over the traditional method of assessing DRAOR total scores.

The proceeding review will first define the terms used to describe the varying factors that influence offending risk. Next, risk assessment as a variable-centered approach will be

considered, specifically the General Personality and Cognitive Social Learning Approach (GPCSL). This approach will be contrasted with the more recent person-centered approach, followed by an overview of previous typology research with assessment measures of risk and need. Finally, a description of the DRAOR will be provided along with a summary of previous research regarding the psychometric properties of the measure.

Factors that Influence Risk

Risk Factors

To understand an individual's level of risk and implement effective programming, knowledge of the most predictive estimates of risk is required. There are generally two types of risk factors: static risk factors and dynamic risk factors (Bonta & Andrews, 2017; Douglas & Skeem, 2005).

Static risk factors are historical predictors of criminal behaviour that are not amenable to intervention. Examples of static risk factors include prior criminal history, past failures while on conditional release, and age at index offence. Static factors are most useful for determining *who* is the most likely to reoffend and are often important in establishing initial levels of risk and supervision intensity (Hanson & Harris, 2000). However, these factors cannot predict *when* an individual is at risk to reoffend, nor typically identify problematic areas to be targeted through intervention (Hanson & Harris, 2000).

Dynamic risk factors (also referred to as *criminogenic needs*; Bonta & Andrews, 2017) are predictors of criminal behaviour that are subject to change, and therefore, amendable to intervention (Brown et al., 2009; Hanson & Harris, 2000). This change corresponds with increases or decreases in recidivism risk (Hanson & Harris, 2000). Dynamic risk factors can be

further subdivided into *stable dynamic* and *acute dynamic factors* (Bonta & Andrews, 2017; Hanson & Harris, 2000).

Stable dynamic factors are enduring patterns of behaviour that change over a long period of time (i.e., months or years; Hanson & Harris, 2000). Examples of stable dynamic factors include holding pro-criminal attitudes, problem-solving, and attachments to others. Due to the persistent nature of stable dynamic factors, it is anticipated that interventions that target these areas would result in sustained changes in risk (Hanson & Harris, 2000). In contrast, *acute dynamic factors* change more rapidly (i.e., over hours or days; Hanson & Harris, 2000) and generally reflect the individual's current circumstance (Bonta & Andrews, 2017). Examples of acute dynamic factors include anger, hostility, negative mood, and access to victims. Examining the dynamic predictors of recidivism have practical relevance, providing a prediction of *when* an individual is at an increased risk of offending and providing target areas for treatment for reducing criminal behaviour (Bonta & Andrews, 2017; Hanson & Harris, 2000; Quinsey et al., 2006; Serin et al., 2019).

Strength-Based Factors

While static and dynamic risk factors tend to explain increases in risk (i.e., how likely an individual is to engage in criminal behaviour), strength-based factors are related to crime desistance (i.e., the process of abstaining from crime) (Polaschek, 2016). Increasingly, strength-based factors are being included within risk assessment measures (e.g., SAPROF; de Vogel et al., 2011) and a plethora of research has been dedicated to uncovering the best way to conceptualize and define these factors (see Ogloff & Davies, 2006; Harris & Rice, 2015; Polaschek, 2016; Woldgabreal et al., 2016; Wanamaker et al., 2018).

Generally, strength-based factors can be internal (e.g., prosocial identity) or external (e.g., social support) factors, that putatively insulate against the opportunistic rewards of criminal behaviour (Bonta & Andrews, 2017; Lösel & Farrington, 2012; Ulrich & Coid, 2011). However, there is ongoing debate related to how strength factors operate in relation to risk. Some researchers suggest that risk is simply the reverse of a risk factor (e.g., having prosocial peers vs. having pro-criminal peers) (Harris & Rice, 2015). While others suggest that identified strengths must be additive, with the potential to decrease the impact of criminogenic risk factors (Scott & Brown, 2018; Lodewijks et al., 2010). For example, Wanamaker et al. (2018) stated that an individual may have pro-criminal peers (i.e., negative influences), prosocial peers (i.e., positive influences), or a combination of the two. However, there may be instances where an individual has no social influences, resulting in a neutral assessment (i.e., no risk or strength present), demonstrating that the absence of risk does automatically suggest the presence of a strength factor (Wanamaker et al., 2018).

Jones et al. (2015) suggested that the term *strength* may be viewed as an umbrella term that encompasses any positive or prosocial aspect of an individual's life. Additionally, Serin et al. (2016) advised that strength factors are largely dependant on individual agency, meaning while a strength factor may be present, this does not automatically suggest that the strength is exercising a positive effect. When presented with an opportunity to engage in criminal behaviour, the individual must be able to choose a non-criminal response (Serin et al., 2016). Further, Brown et al. (2020) argued that the ability of strength factors to add incrementally to risk prediction, above and beyond risk factors, validates their importance. Scholars have demonstrated that integrating strengths with risk assessment increases accuracy and prevents an overestimation of risk (Jones et al., 2015; Ward & Stewart, 2003).

Often, two additional terms are associated with strengths, namely *protective* factors and *promotive* factors. Currently, a *promotive* factor represents an item that negatively correlates with recidivism (i.e., a factor that is related to a positive outcome), regardless of the individual's overall risk level (Farrington, 2003; Farrington et al., 2016). This implies a dose-response relationship with strength factors and offending behaviour, indicating that as the number of strength factors increase, the corresponding level of risk decreases. A *protective* factor, in contrast, is thought to provide a buffering effect, attenuating the impact of risk, specifically for individuals classified as high risk (Lösel & Farrington, 2012; Polaschek, 2016; Farrington et al., 2016). In turn, protective factors are thought to have a minimal effect for those identified as low risk.

Though the debate persists, and there are varying conceptualizations of strength, promotive and protective factors (e.g., Ward, 2017), within the present study, the term *strength* was used as an umbrella term when referring to positive attributes in a justice-involved person's life. Further, when specifically referring to the DRAOR, Wanamaker et al. (2020) have suggested that the six identified protective items may be demonstrating a promotive effect, based on the results of previous research (e.g., Smeth, 2013; Chadwick, 2014). However, they also suggest that more research is warranted before classifying the DRAOR items as promotive or protective. Therefore, to remain consistent with the language of the DRAOR, the term *protective* will be used when discussing the six strength-based items contained within the case management tool.

Variable-Centered Approach

Broadly, different methodological approaches can be classified into variable-centered (e.g., regression, correlation) and person-centered (e.g., mixture modeling analysis) techniques. Variable-centered techniques offer information about the relationship between a set of variables (e.g., suggesting that substance misuse is positively correlated to criminal behaviour) (Schwalbe

et al., 2008). These techniques stem from general theories of criminal behaviour, which seek to explain offending behaviour. One general theory of crime is the General Personality and Cognitive Social Learning theory (GPSCL; Bonta & Andrews, 2017) which informs the widely adhered to guide to correctional treatment; the Risk, Need, Responsivity (RNR) model.

General Personality and Cognitive Social Learning Approach

The General Personality and Cognitive Social Learning Approach (GPCSL) posited that criminal behaviour is driven by the reciprocal relationship between intraindividual characteristics and the external, social environment (Bonta & Andrews, 2017). Furthermore, the variation in one's propensity to commit a criminal act is also dependant on the value placed on the behaviour. Specifically, when the perceived benefits of committing a crime outweigh the costs, the probability that an individual will engage in that behaviour is increased. In contrast, if that view is altered, such that the benefits of prosocial behaviours outweigh the costs of crime, the probability of engaging in crime decreases (Bonta & Andrews, 2017).

Moreover, Bonta and Andrews (2017) suggest that while there are multiple routes or pathways to crime, prominence is given to eight specific social and interpersonal factors that have been empirically determined to increase an individual's propensity to engage in illegal conduct. These factors are termed the *Central Eight* and include one static factor and seven dynamic risk factors. The *Central Eight* include: (1) criminal history; (2) holding pro-criminal or antisocial attitudes; (3) having pro-criminal or antisocial associates; 4) antisocial personality pattern; (5) low-quality family and/or marital relationships; (6) low achievement and satisfaction with school and/or employment; (7) a lack of involvement and fulfillment from leisure or recreational activities; and (8) problematic use of substances (Bonta & Andrews, 2017). Previously, these eight factors were divided into the *big four* and the *moderate four* based on the

strength of their associations with criminal behaviour. However, this distinction has been abolished (Bonta & Andrews, 2016).

The presence of these risk factors increases the likelihood that an individual will engage in criminal behaviour and a plethora of research has provided support for this relationship amongst multiple types of justice-involved individuals including, general offenders (Bonta & Andrews, 2017; Gendreau et al., 1996; Stewart et al., 2017), justice-involved women (Andrews et al., 2012; Simourd & Andrews. 1994; Stewart et al., 2017), and justice-involved adolescents (Onifade et al., 2008; Simourd & Andrews, 1994). In contrast, the positive extremes of each item are considered strengths (e.g., no criminal history, stable employment, prosocial attitudes; Polaschek, 2012). Bonta and Andrews (2017) also assert that other non-criminogenic needs must be considered (e.g., psychopathology, happiness, and self-esteem) as well as situational factors occurring in the environment around them (i.e., someone may be less likely to commit a crime if there is a strong police presence due to the fear of being apprehended).

Overall, the integration of social and interpersonal factors (i.e., the central eight) and cognitive contingencies (i.e., risk and reward) with the GPCSL perspective has provided the core components of many risk assessment instruments as well as the theoretical basis of the RNR model (Andrews et al., 1990). The RNR model is one of the most accepted models for the assessment and effective treatment of justice-involved individuals and has become the preferred approach to correctional programming (Polaschek, 2012; Ward et al., 2007). However, the GPCSL approach is criticized for ignoring the causal mechanisms associated with each identified criminogenic need and how they influence each other to contribute to the onset of criminal offending or recidivism (Heffernan & Ward, 2017). Person-centered approaches may

complement this traditional variable-centered approach to offending behaviour to help fill in this gap.

Person-Centered Approach

Person-centered techniques (e.g., cluster analysis, latent class analysis, latent profile analysis) focus on how groups of individuals are related to each other (Marsh et al., 2009). These techniques offer insight into the unique etiologies of offending behaviour by grouping justice-involved individuals based on a set of shared characteristics, allowing the researcher to uncover "hidden" or "latent" subgroups within large heterogeneous populations (Brushett, 2013; Helfgott, 2008; Oberski, 2016; Williams & Kibowski, 2016). This contrasts with variable-centered approaches that examine the direct relationships between specific variables and probabilities of risk (Wagstaff, 2020), without consideration for individual variation.

Within corrections research, typologies can provide information to influence policies, laws, intervention efforts, and the overall case management of justice-involved individuals (Helfgott, 2008). Helfgott (2008) states three purposes of identifying criminal typologies; to improve management of justice-involved individuals through proper risk classification; to determine appropriate treatment and programming to target specific criminogenic needs; and to develop knowledge regarding the dynamics of specific groups of justice-involved individuals that general theories of criminal behaviour (e.g., GPSCL) do not offer. Within the present study, a person-centered approach will be utilized to uncover groups where the relationship between dynamic risk and strength factors is most salient, to inform correctional intervention and case management strategies. The utility of typologies has emerged as a promising area of study, providing an interesting and innovative way of describing patterns of reoffending across individuals.

Latent Variable Models

Latent Class Analysis (LCA) has become a prominent methodological technique within correctional research for identifying underlying, latent sub-groups within justice-involved populations. Unlike variable-centered methods (e.g., factors analysis) which group items, LCA groups individuals into categories of a latent variable (Nylund-Gibson & Choi, 2018). Latent variables are variables that cannot be directly observed, rather they must be "uncovered" from a set of observed variables (Porcu & Giambona, 2017).

LCA, a branch of finite mixture modeling, was first introduced by Lazarsfeld to classify individuals based on a series of categorical survey responses (Lazarsfeld & Henry, 1968). Since its introduction, various extensions of the model have been developed, allowing for greater flexibility of the technique (Nylund et al., 2007; Porcu & Giambona, 2017). For example, covariates and distal variables can now be examined (Porcu & Giambona, 2017), and continuous indicators can be analyzed through latent profile analysis (LPA) (Oberski, 2016). Within LCA, the latent subgroups (i.e., classes) are identified by the observed responses on a set of indicator variables (Nylund-Gibson & Choi, 2018). Each class is expected to be mutually exclusive, meaning an individual will belong to only one class (Nylund-Gibson, 2018; Oberski, 2016).

LCA offers several advantages over other classification techniques (e.g., *k* means clustering and cluster analysis) as it is model-based, provides information about the likelihood that an individual belongs to a class, provides specific item response probabilities, does not require equal scaling of observed items, and has more formal fit criteria designed for selecting the correct number of classes present within the data (Magidson & Vermunt, 2002; Nylund-Gibson & Choi, 2018).

With LCA, the process of deciding how many classes to retain is often referred to as class enumeration (Nylund-Gibson & Choi, 2018). Group membership is determined by conducting a series of LCAs with differing numbers of class solutions, evaluating a multitude of fit indices (e.g., Bayesian Information Criteria; Schwarz, 1978), and studying the patterns of responses for parsimony, interpretability, and theoretical relevance. It is recommended that when evaluating the number of classes to retain, the researcher should initially run a one-class LCA model and sequentially increase the number of classes being examined, assessing at each step whether the addition of a subsequent class improves the model fit.

Person-centered methods have allowed researchers to gain insight regarding individual differences within populations of justice-involved individuals, in areas such as offending types (e.g., Healy et al. 2016), variations in psychopathy (e.g., Mokros et al., 2015), and antisocial traits (e.g., Driessen et al., 2018). Recently, correctional researchers have begun to explore how justice-involved persons can be categorized based on variations in their risk and need factors, as identified by risk assessment instruments (e.g., Hilterman et al., 2019; Schwalbe et al., 2008; Brown et al., 2020). The proceeding section will discuss examples of typological research conducted with justice-involved individuals based on the distribution of risk and need factors through latent variable methods.

Research with Latent Variable Methods

Correctional researchers have recently begun to focus on classifying justice-involved individuals into various typologies based on risk and need factors (Greiner, 2013). The following provides examples of recent research that have found meaningful groups based on how risk and need factors are distributed throughout their participant samples. Note that a variety of latent variable models will be discussed, and while the terms *clusters, classes,* and *profiles* are often used

interchangeably, there are differences regarding the analyses these terms correspond to. Therefore, for the remainder of this paper, the terms *clusters, classes,* and *profiles* will be used to describe the resultant groups from cluster analysis, LCAs, and LPAs, respectively.

Moreover, the majority of studies conducted in this area have been with samples of justice-involved adolescents (e.g., Simourd et al., 1994), with very few focusing on adults (e.g., Wanamaker, 2020; Seto & Fernandez, 2011). Hence, while the present study included a sample of adults, several studies that focused on adolescents will be discussed. Notably, of those that do include adults, the majority seem to focus on justice-involved individuals who have been convicted of a sexual offence (e.g., Ennis et al., 2016; Miller et al., 2009; Seto & Fernandez, 2011). Finally, given that the present sample only included justice-involved males, studies with female-only samples are not considered (e.g., Cusworth Walker et al., 2016; Odgers et al. 2007).

Seto and Fernandez (2011) utilized two-step cluster analysis to identify different dynamic risk groups amongst a sample of 419 justice-involved male adults (mean age = 42.3), convicted of sexual crimes, who were assessed on the Stable-2000. Four dynamic risk groups were identified: (1) a *low needs* cluster, characterized by low scores on antisociality and sexually deviant items; (2) a *typical* cluster, identified by moderate scores on the majority of antisociality items and low to moderate scores on the sexual deviance items; (3) a *sexually deviant* cluster, who scored high on deviant sexual interests, sexual preoccupation, emotional identification with children, and child molester attitudes; and (4) a *pervasive high-needs* cluster who scored high on both antisociality items and sexual deviance items, suggesting difficulties with general and sexual self-regulation.

Ennis et al. (2016) also utilized cluster analysis to identify subgroups of adult justice-involved males who committed a sexual offence. Their sample included 345 individuals (mean

age = 36.8) who were assessed on the Static-2002R. The resultant clusters were also compared on criminal history (as measured by the Cormier-Lang Criminal History Score; CLS), psychosexual development (as measured by the Childhood and Adolescent Taxon Scale; CATS and the Multiphasic Sex Inventory-2nd edition; MSI-2), sexual attitudes and interests (as measured by the Screening Scale for Pedophilic Interests; SSPI), and their rate of recidivism (occurrence of general, violent, or sexual re-offences) over a two-year follow-up period. Additional variables considered included age at the time of first conviction and experiences of childhood abuse (i.e., instances of physical or sexual assault, neglect, and caregiver inconsistency).

A three-cluster solution was identified; First, a *low risk* cluster, which was identified by having low average Static-2002R scores. Those in this class were considerably older than those in the other classes and tended to be older when they incurred their first criminal conviction. They demonstrated few deviant sexual interests, had a limited criminal history, and were less likely to experience early behaviour and social problems. Second, the *low-moderate risk* cluster, yielded similar Static-2002R scores as the low risk cluster, albeit slightly higher. This class also tended to be younger in age and had a limited criminal history, however, they reported having higher levels of sexual obsession when compared to the other groups. Both the low risk and low moderate risk clusters yielded similar levels of recidivism. Third, the *moderate-high risk* cluster yielded the highest mean scores on the Static-2002R. They had more expansive criminal histories and were more likely to have experienced parental neglect. They were also more likely to have experienced sexual and physical abuse. This cluster also demonstrated the highest levels of recidivism across all types (Ennis et al., 2016). The authors suggested that these classes could inform treatment and supervision practices for those convicted of sexual offences. They stated

that due to the three identified risk levels, justice-involved individuals can be triaged into appropriate programs based on their risk level. Additionally, the researchers advocated that non-sexual criminal needs should be targeted through programming as the rate of non-sexual re-offences was relatively high (Ennis et al., 2016).

Both Campbell et al. (2018) and Brown et al. (2020) sought to determine if meaningful subsets of justice-involved juveniles could be garnered from the Youth Level of Service/Case Management Inventory (YLS-CMI) using LPA. Campbell et al. (2018) utilized a sample of 1, 263 youth probationers who were assessed on the YLS-CMI. Gender (male or female), race (White or Non-White), and age were included as covariates. A three-profile model was identified; 1) the *minimal intervention needs* profile, defined by having the lowest YLS-CMI domain scores; 2) the *social behaviour and social bonding needs* profile, defined by higher scores in the domains of education/employment, family and parenting, and personality and behaviour; 3) the *maximum intervention needs* profile, characterized by a more expansive criminal history, higher levels of substance abuse and a higher overall risk score. Those within the *maximum intervention needs* profile were more likely to be older than those in the *social behaviour and social bonding needs* profile but were similar in age to the *minimal intervention needs* profile (Campbell et al., 2018). Male youth and those who identified as White were more likely to be categorized into the *minimal intervention needs* and *maximum intervention needs* profiles. Finally, the *maximum intervention needs* profile yielded the highest recidivism rates.

The study conducted by Brown and colleagues (2020) used the most recent version of the risk assessment (i.e., the YLS-CMI 2.0). They also examined additional measures and variables related to complex Post Traumatic Stress Disorder (PTSD) (i.e., the Youth Self-Report; YSR; the Adolescent Relationship Scales Questionnaire; ARSQ; The Rosenberg Self-Esteem Scale;

RSES; Adverse Childhood Experiences; ACEs; the Affect Regulation Checklist; ARC; and 12-items related to criminal attitudes and associates). Further, the relationship of recidivism (i.e., any new conviction) to the resultant profiles was explored. Independent LPAs were conducted for males and females. Therefore, only the results for the justice-involved males are discussed. Two profiles were identified: the *complex needs* profile and the *low needs* profile.

Those within the *complex needs* profile yielded higher scores for complex PTSD symptoms including high ACES, low self-esteem, anxious attachments, and emotional and attentional dysfunction. This profile also received high scores across a multitude of criminogenic needs (i.e., violent attitudes, substance misuse, education, family/parenting problems, psychopathy, poor use of leisure time, and criminal associates; Brown et al., 2020). Those within the *low needs* profile demonstrated lower levels across all domains, including both complex PTSD related factors and criminogenic needs. Notably, race was not significantly related to the profiles, however, profile membership was related to recidivism outcomes. The YLS-CMI predicted recidivism outcomes better for the *low needs* profile compared to the *complex needs* profile. Finally, occurrences of new convictions were lower for the *low needs* profile compared to the *complex needs* profile, which had a 73.3% recidivism rate.

Schwalbe et al. (2008) examined a group of 583 (68% male) justice-involved adolescents using LCA to determine if they could be classified into meaningful typologies based on their scores from the Joint Risk Matrix (JRM; a measure of static and dynamic risk). A five-class solution was identified. First, a *low-need* class, which was defined by having the lowest average scores across all items. Second, a *serious school problems* class, which was the largest group, and defined as having low need on most dynamic risk factors, while demonstrating a high need rating in the school behaviour problems domain. Third, a *hostility inattention* class, defined as

having difficulties with hyperactivity and attention, hostility towards others, and cooperation. Fourth, a *high-risk and family history* class was identified. This class was the smallest and was defined by having a high degree of current justice-involved family members. Finally, the fifth class was called s*ubstance abuse and peer delinquency* and had elevated scores on all dynamic risk factors; specific to this class was higher than average scores of substance abuse issues and peer delinquency.

Schwalbe et al. (2008) also examined how varying characteristics (e.g., age and race) were dispersed throughout the classes. It was found that individuals belonging to the low-need class were more likely than all other groups to be first time offenders, while those in the serious school problems class were more likely than the latter three groups to be first time offenders. Those in the hostility inattention group were more likely to be adjudicated for status offences compared to the other classes. Those in the high-risk and family history class were more likely to be Black when compared to other classes. Finally, those in the substance abuse and peer delinquency class were more likely to be older in age and White with a history of running away.

Another study conducted by Miller et al. (2009) explored the utility of LPA to categorize justice-involved adults convicted of sexual offences (128 female; 136 male) into meaningful profiles based on their responses on the Personality Assessment Inventory (PAI). The PAI is composed of 14 scales with a total of 344 items. The measure provides an assessment of personality and psychopathology. Analysis revealed that a four-class model was the best fit for the data. Individuals were divided into the following profiles: (1) a *moderate defensiveness* profile, characterized by slightly elevated scores on the positive impression management scale; (2) an *elevated alcohol and drug use* profile, characterized by clinically significant scores in the alcohol and drug domains and low scores on all other items; (3) a *moderate psychopathology*

profile, characterized by having several scales in the clinically significant range; and (4) an *elevated psychopathology* profile, offenders in this group had clinically significant scores in the majority of scales.

Miller et al. (2009) additionally examined the effect of gender, index offence type (violent or non-violent), and Static-99 scores on profile membership. They found that males were more likely to belong to the elevated alcohol and drug use profile while females were more likely to belong to the moderate psychopathology and elevated psychopathology profiles. Individuals belonging to the elevated psychopathology profile were less likely to have committed a violent index offence when compared to those in the moderate defensiveness profile. Finally, individuals in the moderate defensiveness profile and the elevated drug and alcohol use profile had higher Static-99 scores when compared to the elevated psychopathology profile (Miller et al., 2009).

More recently, Hilterman et al. (2019) conducted an LCA and a Latent Transition Analysis (LTA) (12-month follow-up) to elucidate classes from a sample of 4, 267 male and 661 female justice-involved adolescents assessed on the Structured Assessment of Violence Risk in Youth (SAVRY). The relationship between the resultant classes, criminal history (non-violent and violent), and recidivism (any new charge) was also examined. The LCAs for males and females were conducted independently; therefore, only the male classes are discussed. For the male justice-involved juveniles, a five-class solution was identified.

The *low needs* class, was the largest class, and contained 36% of the sample. This class was identified by low mean scores on all SAVRY risk/need domains. Those within this class had an 89% probability of remaining in this class over the follow-up period. The *low-moderate needs* class was characterized for receiving low mean scores for the items of antisocial behaviour, poor family functioning, and dysfunctional personality traits. They demonstrated high needs in the

area of social support and demonstrated high scores for treatability. Over the follow-up period 14.8% of individuals in this class moved to the *low needs class*. The individuals within this class demonstrated a limited criminal history and were less likely to reoffend when compared to the other classes. The *moderate needs* class was defined by moderate needs in social support, family functioning, antisocial behaviour, and treatability. The *moderate-high needs* class demonstrated high treatability problems and moderate means for antisocial behaviour, dysfunctional personality traits, and social support problems. This class was noted for having a more expansive history of violent offending when compared to the other classes, except for the *high needs* class. Finally, the *high needs* class represented the smallest class and contained 8% of the sample. This class demonstrated multiple difficulties across both the risk and need domains. Over the follow-up period, 13.2% of individuals in this class, moved to the *moderate needs class*. This class was noted for having a more expansive history of violent offending when compared to the other classes, except for the *moderate-high needs* class. This class also demonstrated the highest likelihood of recidivism when compared to the other classes (Hilterman et al., 2019).

Wanamaker (2020) conducted an LPA and LTA to determine if the Service Planning Instrument (SPIn) – Full Assessment would reveal meaningful profiles of justice-involved adults (25, 012 men and 6, 465 women) and if the resultant profiles were stable over time (i.e., over three time points). The LPAs for men and women were conducted independently; therefore, only the male profiles are discussed. The total static risk score (obtained from the SPIn – Full Assessment) and age were entered into the analysis as covariates, while Indigenous status (including First Nations, Metis, or Inuit) was included as an auxiliary variable. Finally, Wannamaker (2020) addressed four recidivism outcomes (i.e., any negative outcome, any new charges, any new violent charges, and technical violations) in relation to the profiles.

A five-profile solution was identified for the justice-involved males that remained stable until the third time point, which yielded an additional sixth profile. First, a *low risk/low strength* profile, defined by overall low scores across risk domains, low mental health needs, few experiences of childhood adversity, and limited criminal history was identified. Across all time points, this profile was noted for having the lowest static risk scores when compared to the other profiles. At timepoint one, this class included a higher proportion of non-Indigenous men compared to Indigenous men. Second, the *aggressive, complex need/low strength* profile was characterized by having multiple risk factors, experiences of childhood adversity, and mental health needs. Those in this profile had higher aggression scores when compared to the other profiles and scored low in the strength domains. Across all time points, this group was noted for higher static risk scores but yielded similar scores to the *low stability, complex need/low strength class* at time point one.

Third, the *moderate risk/moderate strength* profile was the largest profile (33.7%; n = 2, 244) and received moderate scores across all domains. At time point one, nearly half of all Indigenous men (45.91%) were in this profile, and at time point two and three, while the number decreased slightly, this class still demonstrated the largest proportion of Indigenous men. Fourth, the *low risk/high strength* profile received low scores across all risk domains and high scores on all strengths. Fifth, the *low stability, complex need/low strength* profile, was the smallest profile (5.3%; n = 353) and demonstrated the highest scores on multiple dynamic risk domains. The highest scores were noted for the employment risk and stability risk domains. Additionally, this group scored low on aggression and strengths. At time point one, this profile included a higher proportion of Indigenous men compared to non-Indigenous men.

Finally, the sixth profile, the *moderate complex needs/low strength* profile emerged at time point three and was characterized by moderate scores across all risk domains and moderate scores in areas of childhood adversity and mental health. This profile demonstrated low aggression scores and low strengths. Notably, no significant differences in age were found for any of the resultant male profiles and this remained stable over time. Related to recidivism outcomes, the *aggressive, complex need/low strength,* the *low stability, complex need/low strength*, and the *moderate complex need/low strength* profiles appeared to demonstrate the highest reoffence rates.

In summary, Wanamaker (2020) demonstrated the utility of typology research. The LPA yielded five distinct profiles for justice-involved men identified by varying degrees of dynamic risk and strength factors. Further, Wannamaker (2020) captured the dynamic nature of dynamic risk assessments when a new profile emerged at the third time point. While the other five profiles remained stable, this finding suggests that due to the dynamic nature of risk, new profiles demonstrating new patterns of risk and need can emerge over time.

Lastly, Wojciechowski (2020) utilized latent class analysis to elucidate classes composed of varying degrees of risk and protective factors from a sample of 1, 354 justice-involved adolescents. The participants were assessed on a set of five behavioural problems derived from the Psychopathy Checklist-Youth Version, specifically, instances of cheating, stealing, disturbing class, substance use, and fighting before the age of 11. Other indicator variables included two demographic variables (i.e., gender, socioeconomic status), three risk factors (i.e., exposure to violence, deviant peer association, negative affect), and two protective factors (i.e., self-control and social support). Age was entered into the model as a covariate and the relationship of gender and race to the resultant classes was examined.

A three-class solution was considered to best fit the data: 1) a *low early onset of behavioral problems* (low EOPD) class was characterized by a lack of behavioral problems, low scores across risk factors, and high levels of social control; 2) an *FDC early onset of behavioral problems* (FDC EOPB) class, identified by having a higher likelihood of engaging in fights and disrupting class and having moderate scores on both risk and protective factors; and 3) a *DCSF early onset of behavioral problems* (DCSF EOPB) class, who were more likely to engage in all five problematic behaviours of disrupting class, stealing, fighting, cheating, and using substances (Wojciechowski, 2020). This final class also received high scores across all risk factors and low scores across protective factors.

Notably, females were more likely than males to be in the *low EOBP* group, and being male was related to higher offending seriousness (Wojciechowski, 2020). Black offenders were more likely to be represented within the *low EODP* and *FDC EODP* groups while Hispanic offenders were more likely to be in the *DCSF EODP* group. Regarding age, adolescents between the ages of 14 and 19 in the *DCSF EOPB* group engaged in higher severity crime when compared to all other classes. Juvenile offenders between the ages of 20 and 23 in the *DCSF EODP* and the *FDC EODP* groups had similar offence severity rates with both groups being significantly more likely than the low EODP group to report committing higher severity offences (Wojciechowski, 2020).

Overall, the research depicted in this section has provided evidence that large offender samples who are scored on varying risk assessment measures can be meaningfully separated into smaller, more manageable classes or profiles. Based on the distribution of risk and need factors among varying typologies, intervention efforts may be more effective if they are tailored according to group characteristics. Specifically, the studies tended to find a similar pattern of

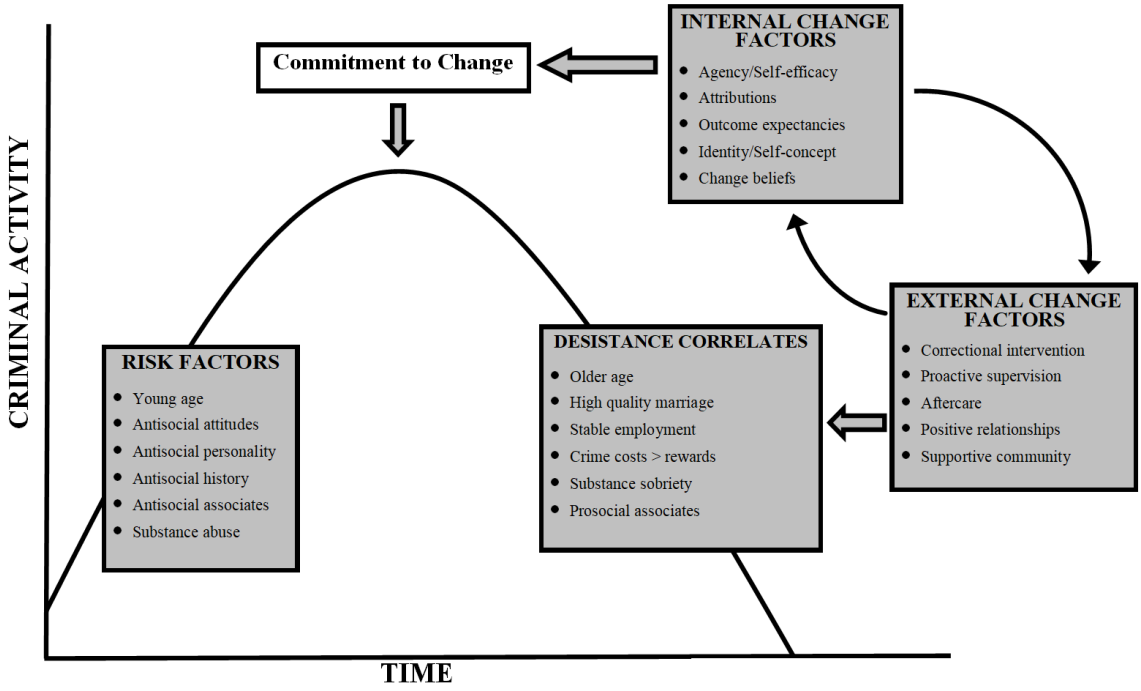
group membership, identifying a low-risk class and a high-risk class, as well as several groups distinguished due to high needs in specific areas (e.g., substance abuse). Those identified as belonging to a general high-needs group would benefit from high intensity programs that target numerous criminogenic needs. In contrast, those within a low needs group would require much less programming, while other identified groups may require specialized programming based on their distinguished pattern of scores. The present study analyzed the DRAOR, an assessment of dynamic risk and protective factors to determine if meaningful classes could be elucidated from a sample of offenders from the state of Iowa.

Dynamic Risk Assessment for Offender Re-Entry (DRAOR)

The DRAOR was developed to assist community supervision officers (i.e., probation and parole officers) in the assessment of justice-involved individuals throughout the transitional period from active offending to a pro-social, crime-free lifestyle. The DRAOR is a 19-item (see Appendix B for item descriptions), interview-based, case management tool designed to inform community supervision officers about factors pertinent to an individual's level of risk. The individual is assessed on the DRAOR at each substantial point of contact, allowing supervising officers to adjust case plans based on real-time changes in risk. The items are conceptually organized into three domains: *stable risk factors* (six items), *acute risk factors* (seven items), and *protective factors* (six items). The measure was developed based on a plethora of research regarding the importance of risk factors (Hanson & Harris, 2000; Bonta & Andrews, 2017) and desistance correlates (i.e., protective factors; Maruna, 2001). Overall, the DRAOR is rooted in a life-course model of offender change (see figure 1; Serin et al., 2010).

Figure 1

Conceptual Model of Offender Re-Entry



Note. From "Enhancing offender re-entry: An integrated model for enhancing offender re-entry" by R.C Serin, C.D. Lloyd, & L.J. Hanby, 2010, *European Journal of Probation, 2*(2), p. 75 (https://doi.org/10.1177/206622031000200205).

Recall that stable dynamic risk factors are susceptible to change but are relatively enduring, with change occurring over a long duration (e.g., months or years). The six *stable* items in this domain reflect attitude, trait, and behavioural patterns and are derived from research reflecting criminogenic needs (Hanson & Harris, 2000; Hanson et al., 2007; Bonta & Andrews, 2016). They include *peer associations* (frequency of time spent with anti-social peers), *attitudes towards authority* (hostility towards authority figures), *impulse control* (highly impulsive), *problem solving* (difficulties finding non-criminal solutions to problems), *sense of entitlement* (inflated self-worth), and *attachment with others* (callous towards others).

The *acute* factors were designed as proximal indicators of risk state (i.e., representing intra-individual changes in risk; Douglas & Skeem, 2005). As mentioned previously, acute risk factors are highly malleable, with change occurring frequently and over shorter periods of time (i.e., hours, days). The seven *acute* factors in this domain reflect situation, mood, and behavioural factors. They include *substance abuse* (problematic substance use), *anger/hostility* (antagonistic, irritability), *opportunity/access to victims* (availability of criminal opportunities), *negative mood* (presence of negative emotions: depression, anxiety, stress, etc.), *employment* (unemployed), *interpersonal relationships* (high conflict or problematic relationships), and *living situation* (lack of accommodation).

The protective domain is comprised of strength factors that exist independent of risk and are thought to change over time (Laub et al., 1998; Serin et al., 2010). These factors act to reduce the individual's propensity to engage in criminal behaviour, even when they encounter a high-risk situation (Serin et al., 2010). The six *protective* factors reflect internal perceptions and social support and were influenced by research pertaining to factors associated with desistance (Maruna, 2001; Sampson & Laub, 2005). They include *responsiveness to advice* (openness to prosocial advice), *prosocial identity* (positive internal self-image), *realistic high expectations* (realistic attitudes about the change process), *costs/benefits of staying crime-free* (favours prosocial behaviours over criminal actions), *social support* (meaningful, prosocial relationships), and *social control* (encouragement and support provided by prosocial others are internalized).

The assessment involves a structured interview between the justice-involved person and the community supervision officer. To ensure fidelity, officers attend training sessions that cover the theoretical background of the DRAOR, the scoring process, and how the information garnered from the measure can be incorporated into the client's case plan. The officers must then apply

their newly acquired skills to a variety of case studies which are then evaluated by the training facilitator. Ultimately, incorporation of a dynamic risk assessment such as the DRAOR in the case management plan offers valuable information beyond what is provided by static risk assessments alone. Static risk measures provide a statistical estimate of risk, evaluating the probability that an individual will, at some point, commit another offence. In other words, it indicates *who* is likely to reoffend (Douglas & Skeem, 2005). In comparison, the dynamic risk assessments consideration of changing factors provides real-time risk-relevant information, related to *when* an individual may be at risk to reoffend, thereby increasing the effectiveness of risk prediction (Douglas & Skeem, 2005; Lloyd et al., 2020).

Psychometric Properties

Past research on the DRAOR has been variable-centered, with an emphasis on how the items are related to each other and if they are predictive of outcome (e.g., factor analysis; Hanby, 2013). Through these methods, the DRAOR has been validated with multiple justice-involved populations, specifically related to general offending (Chadwick, 2014; Hanby, 2013; Lloyd, 2015; Tamatea & Wilson, 2009), high-risk offending (Yesberg & Polaschek, 2015), sexual offending (Smeth, 2013), justice-involved women (Yesberg et al., 2015), and individuals diagnosed with a mental disorder (Wardrop, 2020).

Several studies have used factor analysis to assess the internal structure of the DRAOR (Hanby, 2013; Chadwick, 2014; Yesberg & Polaschek, 2014). The results of the factor analysis studies reveal a debatable factor structure, with a three-factor model (Hanby, 2013), a two-factor model (Chadwick, 2014), and a four-factor model (Yesberg & Polaschek, 2015) identified. However, cross-loadings of stable and acute items can be expected due to the correlation between each of the subscales (Chadwick, 2014).

When considering reliability, acceptable internal consistency estimates have been found for the subscale scores (see Hanby, 2013; Chadwick, 2014). The majority of the DRAOR items are found to be moderately to strongly correlated with their respective subscale scores (see Chadwick, 2014), and inter-rater reliability has been satisfactory (Wilson, 2011; Smeth, 2019). Additionally, the DRAOR has demonstrated convergent validity with other assessments of risk, including the RoC*RoI (Bakker et al., (1998), the Static-99R (Helmus et al., 2012), the Automated Sexual Recidivism Scale (ASRS; Skelton et al., 2006) and the Violence Risk Scale (VRS; Wong & Gordon, 2000) (Averill, 2016; Chadwick, 2014; Hanby, 2013; Smeth, 2013; Tamatea & Wilson, 2009; Yesberg & Polaschek, 2015).

Moreover, research has provided evidence to suggest that the DRAOR is predictive of recidivism outcomes. For brevity, the majority of studies that have examined the predictive validity of the DRAOR are summarized in Table 1. Ultimately, the present study adds to this growing body of research by examining item-level differences between classes of justice-involved individuals assessed on DRAOR and suggesting direct targets for programming and intervention.

Table 1

The Predictive Utility of the DRAOR on Recidivism Outcomes

			Stable		Acute		Protective	
Source	Sample	Outcome	*r*	*AUC* [95% CI]	*r*	*AUC* [95% CI]	*r*	*AUC* [95% CI]
Serin & Prell (2012)	General offenders [I]	Technical violations or new offences	.23	.60 [.56, .64]	.25	.65 [.61, .69]	-.28	.67 [.63, .70]
		New offences only	.12	-	.11	-	-.15	-
Hanby (2013)	General offenders [NZ]	Technical violations or new offences	.29	.66 [.65, .68]	.38	.72 [.70, .74]	.29	.67 [.65, .68]
		New offences only	.21	.62 [.60, .64]	.29	.67 [.65, .69]	.21	.62 [.60, .64]
	Maori offenders [NZ]	Technical violations or new offences	.26	.65 [.62, .67]	.35	.70 [.68, .72]	.26	.65 [.62, .67]
		New offences only	.21	.61 [.59, .64]	.27	.66 [.63, .68]	.20	.61 [.58, .64]
Smeth (2013)	Male sex offenders [I]	Technical violations	.33	.69 [.62, .78]	.27	.65 [.57, 74]	-.18	.61 [.52, .69]
		Sexual recidivism	.01	.51 [.26, .75]	.05	.53 [.30, .75]	.01	.46 [.21, .71]
Chadwick (2014)	General offenders [I]	Technical violations or new offences	-	.62 [.56, .67]	-	.59 [.54, .65]	-	.58 [.52,.64]
		New offences only	-	.52 [.42, .62] ^{ns}	-	.53 [.43, .63] ^{ns}	-	.56 [.47, .66] ^{ns}
Yesberg & Polaschek (2015)	High-risk male offenders [NZ]	Technical violation	-	.53 [-,-]	-	.53 [-,-]	-	.58 [-,-]
		New conviction	-	.61 [-,-]	-	.57 [-,-]	-	.60[-,-]
		New violent conviction	-	.58 [-,-]	-	.55 [-,-]	-	.61 [-,-]
		Reimprisonment	-	.59 [-,-]	-	.60 [-,-]	-	.62 [-,-]
Fergusson (2015)	Male adolescent offenders [NZ]	Criminal revocation	-	.61 [.49, .73]	-	.60 [.48, .71]	-	.60 [.48, .71]
Averill (2016)	Sexual offenders [NZ]	Technical violations or new offences	.33	-	.39	-	.33	-
		Sexual recidivism	.02^{ns}	-	.07		.06^{ns}	

			Stable		Acute		Protective	
Source	Sample	Outcome	*r*	*AUC* [95% CI]	*r*	*AUC* [95% CI]	*r*	*AUC* [95% CI]
Muirhead (2016)	Adolescent offenders [NZ]	Any reconviction	-	.70 [.64, .76]	-	.69 [.63, .74]	-	.68 [.62, .74]
Serin et al., (2016)	General offenders [I]	Technical violations	-	.66 [.60-.72]	-	.68 [.62-.74]	-	.70 [.65-.76]
		Serious violations	-	.66 [.60-.73]	-	.70 [.63-.77]	-	.70 [.64-.76]
		New crime	-	.67 [.59-.75]	-	.68 [.59-.77]	-	.67 [.59-.75]
Wardrop (2020)	Offenders without a mental illness [I]	Technical violations and any new offence	-	.69 [.64, .74]	-	.63 [.58, .68]	-	.65 [.60, .70]
		New offence only	-	.67 [.61, .73]	-	.62 [.55, .68]	-	.63 [.56, .79]
	Offenders with a mental illness [I]	Technical violations and any new offence	-	.55 [.50, .60]	-	.55 [.50, .61]	-	.53 [.47, .58]
		New offence only	-	.51 [.45,.57]	-	.53 [.46, .59]	-	.49 [.42-.56]

Note. Four additional studies evaluating the predictive validity of the DRAOR were omitted due to incompatible statistics (Lloyd, 2015; Lowenkamp, Johnson, Trevino, & Serin, 2016; Tamatea & Wilson, 2009; Yesberg et al., 2015). [I] = Iowa sample; [NZ] = New Zealand sample; r = point-biserial correlations; AUC = area under the curve statistics; 95% CI = 95 % confidence interval; "-" = statistic absent. p = <.05 unless otherwise specified (ns).

Present Study

The present study examined the potential utility of a person-centered approach to risk assessment and prediction. Specifically, justice-involved males assessed on the DRAOR at a single time point (baseline assessment) were evaluated to determine if distinct classes could be derived from the dynamic need and protective factors. To date, there has been no research conducted in this area with the DRAOR. If a set of classes emerge, indicating that specific risk and protective factors cluster among subsets of justice-involved individuals, case management practices (i.e., supervision practices and intervention strategies) could be adapted and enhanced as a result.

Research Questions

Research Question 1. Can meaningful typologies be delineated among justice-involved males in Iowa, using dynamic and protective variables derived from the DRAOR?

Hypothesis 1. Given that this was the first study exploring the utility of classes based on DRAOR assessment scores, a specific number of classes was not estimated. However, previous research involving the study of dynamic and strength factors has found the presence of between three and six classes (Wanamaker, 2020; Perkins, 2010). It was hypothesized that several groups would emerge based on varying needs with respect to the 19 DRAOR items. The resultant classes were considered meaningful if they were highly distinguishable from each other in terms of item scores. These differences would indicate specific domain targets for correctional programming that extend beyond having a group deemed low risk, moderate risk, or high risk (which would support a variable-centered approach). For example, a group that is identified by a high need in the items related to social relationships (i.e., peer associations, attachment with others, and interpersonal relationships, social support and social control) would require specific

programming related to developing and maintaining social relationships rather than focusing on non-problematic areas (e.g., impulse control or problem solving).

Research Question 2. Is class membership related to the IRA static risk scores?

Hypothesis 2. Recall that the DRAOR is a tool that measures both dynamic risk and protective factors. These factors are subject to change and are amenable to treatment, providing the ability to detect a change in an individual's risk level and allowing evaluators to ascertain *when* the individual is likely to re-offend (Hanson & Harris, 2000; Andrews & Bonta, 2006; Brown et al., 2009; Lloyd et al., 2020). In contrast, static risk is highly invariable, representing a separate construct of risk that is beneficial when determining *who* is likely to re-offend (Hanson & Harris, 2000). It was hypothesized that the IRA static risk scores would be related to class membership. Specifically, resultant classes designated as high in dynamic need and low on protective factors were predicted to have higher static risk scores. In contrast, those rated lower in dynamic need and higher in protective factors were predicted to have lower static risk scores.

Research Question 3. Is class membership related to the demographic variables of age and race?

Hypothesis 3A. Previous research on risk and need with justice-involved populations have found mixed results regarding the distribution of age across typologies with some finding no significant differences in distributions across classes/profiles (Lloyd et al., 2019; Wannamaker, 2020; Wagstaff, 2020; Brown et al., 2020) and some suggesting that there are age differences (Campbell et al., 2019; Schwalbe et al., 2008; Wojciechowski, 2020). Notably, the majority of the aforementioned studies were conducted with justice-involved adolescents resulting in restricted age ranges. Despite these mixed results, the relationship between age and crime has been established within correctional research (Farrington, 1986; Gottfredson &

Hirschi, 1993; Moffitt, 1993; Piquero et al., 2008). For example, Higley et al. (2019) posited that age can be considered a specific responsivity factor. While not a direct risk factor, age may attenuate the effect of risk on recidivism. Higley et al. (2019) found, with a sample of violent, justice-involved males in Canada, older participants (i.e., mid-to-late 30s and above) had lower likelihoods of recidivism and higher levels of program performance when compared to younger participants. Given the age range of the current sample (i.e., 17 to 78), it was hypothesized that there would be differences in the distribution of age across classes. Additionally, in line with the age-crime curve (i.e., beginning to engage in criminal activity in early adolescence, experiencing a peak in offending behaviour, and desisting thereafter; Gottfredson & Hirschi, 1993) it was hypothesized that those who were rated as lower in dynamic risk would be older, while those rated as higher in dynamic risk would be younger.

Hypothesis 3B. Pertaining to the examination of racial distribution within typology research, a substantial number of studies have suggested differences in the distribution across classes/profiles (Schwalbe et al., 2008; Campbell et al., 2019; Ford et al., 2013; Cusworth Walker, 2016; Wagstaff, 2020; Wannamaker, 2020) while others have found no differences in racial distribution (Brown et al., 2020; Charak et al., 2019). Notably, barring Wannamaker (2020), the aforementioned research has focused on justice-involved youth. Additionally, while Wanamaker (2020) focused on a sample of justice-involved adults, differences in racial distribution across profiles were only found for adult women but not adult men. Therefore, there were no specific hypotheses stated concerning the distribution of race across classes.

Research Question 4. Do recidivism rates vary as a function of class membership?

Hypothesis 4. Previous research with the DRAOR has found the measure to be predictive of both technical violations (Chadwick, 2014) and any revocation (Hanby, 2013). Additionally,

prior typological research based on risk assessment has demonstrated that recidivism rates can vary as a function of resultant latent groups (Campbell et al., 2019; Hilterman et al., (2019); Wagstaff, 2020; Wanamaker, 2020). Therefore, it was hypothesized that the relationship between recidivism outcomes and the DRAOR scores would vary across classes.

Research Question 5. Is the predictive validity of the DRAOR related to class membership, and does the predictive validity of the classes exceed that of the DRAOR total score (i.e., overall sample)?

Hypothesis 5. There appears to be limited research to date on the predictive utility of latent groups for recidivism. However, Wagstaff (2020) did find that that the predictive accuracy of recidivism varied as a function of the latent profiles when examining a risk, need, and strength-based assessment (i.e., the YASI) in a sample of justice-involved male youth. It was hypothesized that the resultant classes would predict recidivism similarly or better than using DRAOR total scores alone. By addressing whether a specific set of classes emerge from DRAOR test scores, predictive accuracy may improve for the separate groups beyond total DRAOR scores. Ultimately, the association between typological structure and criminal outcomes would be important for guiding offender case management and treatment. It was also expected that the DRAOR would perform better for those who scored high on dynamic need and low on protective factors, compared to those who scored low on dynamic and high on protective factors.

Methodology

Procedure

Archival pilot data from the implementation of the DRAOR was provided by the Iowa Department of Corrections to be used within the present study. The pilot was implemented in August 2010 with a group of 36 community supervision officers who volunteered to be trained.

Following the completion of the pilot, state-wide implementation of the community supervision tool began in 2011. The use of the DRAOR was formally included within the Iowa Department of Corrections policies in April 2015.

Within the present dataset, each participant had at least one completed DRAOR assessment. All data, including demographic information and DRAOR scores, were provided electronically. Participants were assessed on the DRAOR between March 2011 and July 2011, allowing for an approximately 4.5-year follow-up.

Participants

A total sample of 510 justice-involved males on community-based release in the state of Iowa was used within the present study. This cohort consisted of the individuals originally included in the DRAOR pilot study, which validated the use of the tool in the state of Iowa (Chadwick, 2014). While there have been studies conducted on larger sample sizes since the pilot (see Wardrop, 2020 (n = 961) for example), the current sample was used to ensure fidelity. Prior to delivering the DRAOR assessment, the community supervision officers attended in-person training sessions which covered the theoretical background of the DRAOR, the scoring process, and how the information garnered from the measure could be incorporated into the client's case plan. The officers then applied their newly acquired skills to a variety of case studies which were evaluated by the training facilitator. Given the thorough training received, it is believed that this sample provided greater scoring veracity.

Preliminary descriptive analysis revealed that the mean age of the sample at the time of the DRAOR assessment was 32.33 (SD = 11.95) ranging between 17 to 78 years. There was considerable variation in how long they had been on supervision prior to the DRAOR assessment. The average length of time on supervision before the assessment was approximately

one year (*M* = 347.30 days, *SD* = 368.68) ranging between 0 to 2431 days. The community supervision officers selected which justice-involved to assess on the DRAOR. They may have felt more comfortable doing initial assessments with individuals who had been on community supervision for some time, rather than focusing on new clients. Additionally, focusing on these clients may have increased the amount of information required to complete the assessment. However, this may raise concerns about whether this DRAOR assessment truly represented a baseline assessment.

The sample predominantly identified as White (71%; *n* = 362), followed by Black (28.8%; 147), and Asian or Pacific Islander (.2%; *n* = 1). The majority were serving a probation sentence (80.9%; *n* = 413; i.e., serving a community sentence as an alternative to incarceration), identified as single (59.2%; *n* = 303) and had received a high school diploma or GED (62%; *n* = 318). According to DRAOR total cut-off scores, intended to inform intervention efforts (Serin & Chadwick, 2017), 7.8% (*n* = 40) were classified as low risk, 36.9% (*n* = 188) were moderate risk, 54.5% (*n* = 278) were moderate/high and 1% (*n* = 4) were high risk. The majority (64.9%) of the sample fell into the highest two categories on the IRA (46.7% intensive, 18.2% high normal). Complete breakdown of the sample demographics can be viewed in Table 2.

Table 2

Sample Demographic Information (n = 510)

Demographic information		% (*n*)
Marital status	Single	59.4 (303)
	Divorced	9.4 (48)
	Married	16.3 (83)
	Common-law	1.4 (7)
	Unknown	13.5 (69)
DRAOR risk level	Low	7.8 (40)
	Moderate	36.9 (188)
	Moderate/high	54.5 (278)
	High	1 (4)
IRA supervision level	Administrative	6.5 (33)
	Minimum	11.6 (59)
	Low normal	17.1 (87)
	High normal	18.2 (93)
	Intensive	46.7 (238)
Race	Caucasian	71% (362)
	Black	28.8% (147)
	Asian or Pacific Islander	.2% (1)
Highest education level	High school or GED	62.3% (318)
	GED	32.7% (167)
	Less than high school [a]	24.7% (126)
	Some college [b]	2.7% (14)
	College degree [c]	2.9% (15)
	Technical training completion [d]	1.8% (9)
	Special education diploma	1.0% (5)
	Unknown	4.5% (23)
Supervision status	Parole [e]	5.9% (30)
	Probation [f]	80.9% (413)
	Work release	8.6% (44)
	Pretrial release with supervision	4.5% (23)

Note: DRAOR = Dynamic Risk Assessment for Offender Re-Entry, IRA = Iowa Risk Assessment [a] Includes grades 6, 7, 9, 10, 11, and 12. [b] includes those in college at the time of assessment, and those who completed their freshman, junior, or sophomore level college. [c] Includes associate's, bachelor's, and master's degrees. [d] Includes technical training completion and vocational program/technical certificate. [e] Includes Interstate Compact Parole. [f] Includes Special Sentence and Interstate Compact Probation offenders.

Measures

Dynamic Risk Assessment for Offender Re-Entry (DRAOR)

The DRAOR is a structured professional judgement tool, developed to assist community supervision officers (i.e., probation and parole officers) in the assessment, and reassessment, of justice-involved individuals with reference to their (1) stable risk factors, (2) acute risk factors and (3) protective factors, to inform case management in terms of offender risk and intervention strategies. The stable subscale includes six items: peer associations, attitudes toward authority, impulse control, problem-solving, sense of entitlement, and attachment with others. The acute subscale includes seven items: substance abuse, anger/hostility, opportunity/access to victims, negative mood, employment, interpersonal relationships, and living situation. Finally, the protective subscale includes six items: responsiveness to advice, prosocial identity, realistic high expectations, costs/benefits supportive of staying crime-free, social support, and social control (see Appendix B for item descriptions).

Each item on the DRAOR is scored on a three-point scale (0, 1, 2). For each dynamic risk item (*stable* and *acute*), a score of zero indicates *no problem*, a score of 1 indicates a *slight or possible problem* and a score of two indicates a *definite problem*. For the protective subscale, a score of zero indicates that the item is *not an asset* (i.e., does not demonstrate a protective effect), a score of one indicates that the item is a *slight or possible asset*, and a score of two indicates that the item is a *definite asset*. For research purposes (i.e., assessing the predictive utility of the DRAOR), subscale scores are generated by summing each item in the subscale, resulting in scores ranging between 0 and 12 for the *stable* and *protective* domains and between 0 and 14 for the *acute* domain. Total scores are then generated by summing the scores from the *acute* and *stable* domains and subtracting the *protective* domain. Total scores range from -12-26.

Based on the total scores, clients are assigned to a corresponding risk category. Serin and Chadwick (2017) have recently developed cut-off scores (see Appendix A) which provide a guide for community supervision officers to alter the client's supervision intensity level by categorizing them into one of four risk levels (i.e., low, moderate, moderate/high, high). Specifically, the initial supervision level an individual receives based on a static risk assessment should decrease by one level if DRAOR total scores are low, increase by one level when total scores are moderate/high or high, and remain unchanged if total scores are moderate (Serin & Chadwick, 2017). As the DRAOR is a measure of dynamic risk, it is recommended that clients are reassessed during every substantive contact with their supervising officer (Chadwick, 2014). Within the present study, only the first assessment was considered to maximize sample size. Overall, the DRAOR is used to inform case planning, level of supervision, and intervention management strategies.

Iowa Risk Assessment (IRA).

The IRA is an actuarial assessment tool developed by the Iowa Department of Corrections to assist evaluators in identifying the justice-involved person's community supervision level (Chadwick, 2014). The IRA is comprised of 13 items that measure static risk. Examples of these items include age at first conviction, number of prior convictions, prior community supervision periods, number of past revocations, and alcohol misuse and drug problems. The item scores are summed together to reach a total score ranging from -5 to 25. The total score informs the recommended level of supervision. If there are extraneous variables to consider, the officer may override the results. Specifically, scores between -5 and 1 are assigned to administrative supervision, scores between 2 and 7 result in a minimum supervision level, scores between 8 and 11 result in a low normal supervision level, scores between 12 and 14

result in a high normal supervision level, and scores 15 and above result in an intensive supervision level.

Previous research regarding the predictive utility of the IRA with justice-involved males in Iowa has demonstrated that total scores are predictive of recidivism outcomes, specifically any new crime or revocation (*AUC* = .73) and any new violent crime (*AUC* = .69; Prell, 2013). Furthermore, Serin et al. (2018) used univariate cox regression analysis to examine the predictive validity of the IRA. They found that the IRA was able to significantly predict both the time to first technical violation and time to a new offence. While the IRA is not the primary focus of the present study, it was included as a covariate within the analysis to determine how levels of static risk relate to class membership.

Recidivism

Overall, recidivism referred to any negative outcome that occurred post-DRAOR assessment. Five specific types of recidivism were examined independently: *any negative outcome, any new offence, any new non-violent offence, any new violent offence*, and *any technical violation*. The re-offence rates for all outcomes are presented in Table 3. All variables were coded dichotomously (0 = No; 1 = Yes). The follow-up time for recidivism ranged from 0 days to approximately 4.5 years. The following provides descriptions of each of the outcomes.

1) Any negative outcome (s): this outcome included any failure while on community release including both new offences and technical violations (i.e., any recidivism).
2) Any new offence (s): This outcome excluded technical violations but encompassed both new violent and non-violent offences, in other words, this variable reflected any instance of incurring a new criminal charge.

3) Any new non-violent offence (s): This outcome excluded both technical violations and any new violent offences, thereby only including instances where an individual incurred a new charge for a non-violent offence.
4) Any new violent offence(s): This outcome excluded both technical violations and any new non-violent offence, thereby only including instances where an individual incurred a new charge for a violent offence.
5) Any technical violation(s): This outcome included only technical violations or breaches of community release conditions and excluded any charges related to committing a new offence.

Table 3

Recidivism Outcome Rates for Iowa Sample (n = 510)

Outcome	%(*n*)
Any negative outcome	69.80 (356)
Any new offence	38.00 (194)
Any new non-violent offence	27.10 (138)
Any new violent offence	11.00 (56)
Any technical violation	64.90 (331)

Note: Given that technical violations do not always result in a return to prison, individuals who have had a technical violation may be also classified within the new offence categories. Specifically, of those who received a technical violation, 51.1% (*n* =169) also incurred a new criminal charge.

Analytic Plan

The LCA was performed using Mplus version 8.5 (Muthén & Muthén, 1998-2017), while follow-up analyses were performed using Statistical Software Package for the Social Sciences Statistical Approach (SPSS) version 25, and MedCalc version 19.8 (MedCalc Software Ltd., 2021). Preliminary analyses were conducted to identify potential data errors and the presence of outliers and to assess normality, linearity, and homogeneity.

Phase One: Latent Class Analysis

Phase one addressed whether meaningful classes based on risk and strength factors could be derived from the DRAOR. Mplus version 8.5 (Muthén & Muthén, 1998-2017) was used to conduct the LCAs with the 19-DRAOR items, which were classified as indicator variables. Indicator variables directly inform the formation of the classes.

Recall that LCA is a person-centered statistical method that is used to identify a set of classes (i.e., sub-groups) of an unobservable, underlying construct (i.e., latent variable) with data obtained from cross-sectional designs (Piquero et al., 2015; Williams & Kibowski, 2016). Individuals within each class have comparable characteristics, while differences between classes are maximized (Miller et al. 2009; Vermunt & Magidson, 2002).

Furthermore, LCA allows for multiple choices of formal cluster criteria which can be considered with underlying theory, leading to less arbitrary decisions when selecting the optimal model (Marsh et al., 2009). While there is no current consensus on the best criteria to determine the correct number of classes (Porcu & Giambona, 2017), researchers use a combination of criteria in conjunction with substantive theory to guide the decision (Nylund et al., 2007). Therefore, multiple indicators of model fit were used to determine the correct number of classes to be included in the final model. Specifically, the Akaike's Information Criterion (AIC; Akaike, 1987), the Bayesian Information Criteria (BIC; Schwarz, 1978), the sample size adjusted Bayesian Information Criteria (ABIC; Sclove, 1987) the Lo-Medell-Rubin test (LMR; Lo et al., 2001), the bootstrap likelihood ratio test (BLRT; McLachlan and Peel, 2000) and entropy.

The AIC is an estimate of divergence, it provides a measure of the difference between a specified model and a true model (Vrieze, 2012). Generally, lower AIC values indicate better model fit. Notably, the AIC is criticized for being an inconsistent model fit measure that lacks

parsimony constraints, resulting in more variation in the values, and potentially overestimating the class solution (Ferguson et al., 2020; Nylund et al., 2007).

The BIC provides a measure of similarity between an estimated probability distribution and the probability distribution from the true model (Vrieze, 2012). The ABIC is similar to the BIC, however, it adds a penalty to prevent overfitting of the model (Tein et al., 2013). Lower values of the BIC and ABIC indicate the preferred model, accounting for both model fit and parsimony. However, the BIC is criticized for being too conservative, due to the value placed on parsimony (Nylund, 2007). Nonetheless, simulation studies have demonstrated that the BIC tends to outperform other information criteria when there are a larger number of indicators (i.e., more than 10) within the model (Morgan 2015, Nylund et al., 2007).

The LMR allows for a comparison of the improvement of fit between neighbouring class solutions, specifically, whether the $k - 1$ class model is a better fit to the data compared to a k class model, indicating if there is a significant improvement in fit with the inclusion of each additional class (Williams & Kibowski, 2016; Nylund et al., 2007). Simulation studies have shown that in instances where the LMR incorrectly identifies a class model, there tends to be an overestimation of the number of classes present within the data (Nylund et al., 2007). This suggests that when the LMR is significant, the researcher can be relatively certain that the significant value is representative of the highest number of classes present within the data.

The BLRT is a likelihood-ratio test that uses bootstrapped samples to estimate the distribution of the log-likelihood values (Nylund et al., 2007). Similar to the LMR, the BLRT also compares the model fit between the k model and the $k - 1$ model, to determine the best-fitting model. The BLRT has been considered to be the best indicator of model fit for LCA models (Nylund et al., 2007), however, both the LMR and the BLRT are criticized for never

reaching a significant value when there are a large number of parameters in the model (Ferguson et al., 2020).

Finally, entropy provides a measure of the estimated probability of each individual belonging to a specific class. Entropy values range from 0 to 1, with values closer to 1 indicating a clear separation of classes (Asparouhov and Muthén, 2018) and values closer to 0 indicating uncertainty in the model (Ferguson et al., 2020). Generally, values of .80 or higher are considered acceptable evidence that the classes are well separated (Tein et al., 2013).

Overall, a lower BIC, ABIC, and AIC, higher entropy, and significant LMR and BLRT tests indicate the best fitting model, revealing the class structures. However, it is common that the fit criteria do not converge on the same model (Nylund et al., 2007). In these instances, the researcher must consider the fit indices in combination with how each of the classes are related to each other (i.e., are the classes truly distinct from one another based on the distribution of scores?), the parsimony and interpretability of the class solution (i.e., are the differences between classes clear and easy to interpret), and if the resultant classes are supported by prior theory.

Phase Two: Covariate and Distal Variables

Phase two focused on the second and third research questions and explored the relationship of the external variables (IRA static risk scores, age, and race) to the latent variable. Oftentimes it is useful to examine how exogenous variables that are identified outside of the primary indicators (i.e., the DRAOR items) relate to latent class membership (Nylund & Choi, 2018). Researchers must make judgement calls regarding how these external variables should be incorporated into the model (Ferguson et al., 2020). Specifically, these variables can be entered into the model as covariates or distal outcome variables (often referred to as auxiliary variables due to the use of the “auxiliary” command in the Mplus software). Both covariates and distal variables provide additional information about the emergent latent classes.

Covariate. The IRA static risk scores were entered into the model as a covariate. When covariates are entered directly into the model, the latent class variable is concurrently regressed on the covariates (Clark and Muthén, 2009; Nylund-Gibson & Masyn, 2016). The observed associations between the covariate and the latent class variable are explained by the covariates' indirect effect on the indicators through the latent class. The formation of the classes and therefore, the substantive interpretation of the classes, is changed as a result (Nylund-Gibson & Masyn, 2016). The inclusion of covariates into the model should be based on substantive theory, which allows the research to know, a priori, that the covariate is related to the indicators (Clark and Muthén, 2009). In this manner, the addition of covariates can improve classification accuracy (Lubke & Muthén, 2007). Within the current study, IRA scores were included as a covariate to ensure that the level of risk based on historical risk factors, not captured by the DRAOR, was considered. In addition to including these variables in the LCA, analysis of variance (ANOVA) and multinomial categorical regressions were conducted to examine the relationship between the LCA classes and the static risk scores.

Distal Variables (Auxiliary). To determine if class membership was related to the demographic variables of age and race, both variables were included in the model as distal or auxiliary variables. Unlike covariates, distal variables are not used directly in the analytic model and do not influence class membership (Clark and Muthén, 2009; Nylund-Gibson & Choi, 2018; Nylund et al. 2019). Distal variables are examined once the best fitting model is selected to determine if the latent classes display mean-level differences in the selected distal variables (Nylund-Gibson & Choi, 2018). Often, distal variables are conceptualized as "consequences" of class membership, meaning that while they do not contribute to the formation of the classes, they provide additional information about their composition (Nylund et al., 2019).

Methodological researchers have suggested numerous ways of incorporating auxiliary variables into the LCA analysis to ensure they do not impact the formation of the classes (e.g., the classify-analyze approach, ML three-step approach, and the BCH method; for in-depth reviews of these approaches and others see Nylund-Gibson et al., 2019; McLauren & O'Neill, 2018; No & Hong, 2018). Currently, simulation studies have recommended the use of the Bolck-Croon-Hagenaars (BCH; Bolck et al. 2004) approach (Asparouhov & Muthén, 2014; Bakk et al., 2013; No & Hong, 2018). Therefore, this method was utilized in the present study. Finally, to examine the relationship between the variables of age and race and the resultant classes, chi-square analyses were conducted.

Phase Three: Recidivism Outcomes

Phase three addressed the fourth research question, which explored whether class membership was related to instances of recidivism. Five binary recidivism outcomes (i.e., any negative outcome, any new charge, any new non-violent charge, any new violent charge and any new technical violations) were analyzed as distal variables. The recidivism outcomes were included in the model using the BCH approach to ensure they did not influence class membership. Chi-square tests were conducted to examine the relationship between the recidivism outcomes and the resultant LCA classes.

Phase three also addressed the fifth research question, to explore how the DRAOR scores for the resultant classes compared to the DRAOR scores for the overall sample regarding the prediction of the recidivism outcomes. Receiver operating characteristic (ROC) analysis and area under the curve (AUC) statistics were calculated to evaluate the predictive accuracy of the DRAOR total scores and the latent classes with respect to the five outcomes. AUC is a common discrimination statistic that allows the probabilistic prediction that a randomly selected recidivist

will have a higher score compared to a randomly chosen non-recidivist (Helmus & Babchishin, 2017). AUCs range from 0 to 1, with values above .50 indicating positive predictive accuracy (i.e., higher rates of recidivism) and values lower than .50 indicating negative predictive accuracy (i.e., lower rates of recidivism). An AUC value of .50 indicates that the predictive accuracy is no greater than chance. Within social science literature (Rice & Harris, 2005), an AUC value of .54 is representative of a small effect, while .64 is moderate, and .71 is large.

Comparisons between the DRAOR total scores and LCA classes were then calculated using MedCalc version 19.8 (MedCalc Software Ltd., 2021), which uses the method described by Hanley and McNeil (1983). This test statistic assesses whether two AUC values are significantly different from each other when two or more ROC curves are generated from the same sample. It accounts for the potential correlation between each of the AUCs by calculating the standard error of the difference between the two AUC values. A significant critical ratio *Z* indicates that the two AUC's are significantly different from each other.

Results

Preliminary Analyses

Descriptive information for the DRAOR items and total scores is displayed in Table 4. There were no missing data for any of the 19 indicator variables used for the class enumeration process. There were no missing data for the covariate IRA score or distal variables of age and race, however, out of the 510 justice-involved males, 71% (n = 362) identified as white, 28.8% (n = 147) identified as Black, and only .2% (n = 1) identified as Asian or Pacific Islander, therefore the latter two groups were collapsed into one group and labelled People of Colour (POC). The continuous variables of IRA static risk score, age, and DRAOR total scores were examined for normality using the Kolmogorov-Smirnov test as well as visual inspection of the

data (i.e., histograms and normal Q-Q plot). Results suggested that the DRAOR total scores departed from normality, however visual inspection of the data determined that this departure was not vast. Additionally, both the IRA static risk score and age were negatively skewed and this departure from normality was supported by the visual inspection of the data. These variables were still treated as normally distributed continuous variables, as latent classes models are assumed to contain a variety of normal distributions within the data (Kreuter & Muthén, 2008). Further, chi-square analysis requires at least five expected frequencies within each group of the categorical variable and at least 10% frequencies in any one category of the dichotomous variables. These assumptions were never violated, however, the recidivism outcome of any new violent offence had a frequency of 11% (n = 56) for those who committed a new violent offence, given this low base rate, the results of this variable were interpreted with caution.

Table 4

Means for Each of the DRAOR [a] Derived Indicator Variables and DRAOR Total Scores

Indicator variables and total scores	*N* = 510	
	M (*SD*)	Range
Stable items		
Peer associations	.98 (.55)	0-2
Attitudes toward authority	.66 (.62)	0-2
Impulse control	.94 (.65)	0-2
Problem-solving	.90 (.59)	0-2
Sense of entitlement	.64 (.63)	0-2
Attachment with others	.67 (.56)	0-2
Acute items		
Substance abuse	.79 (.76)	0-2
Anger/hostility	.62 (.67)	0-2
Opportunity/access to victims	.69 (.65)	0-2
Negative mood	.69 (.65)	0-2
Employment	.87 (.85)	0-2
Interpersonal relationships	.91 (.62)	0-2
Living situation	.82 (.65)	0-2
Protective items		
Responsiveness to advice	1.17 (.56)	0-2
Prosocial identity	1.09 (.54)	0-2
Realistic high expectations	1.15 (.65)	0-2
Costs/benefits of staying crime-free	1.14 (.59)	0-2
Social support	1.16 (.63)	0-2
Social control	.98 (.60)	0-2
Total scores	3.49 (7.43)	-12 - 26

Note. [a] DRAOR = Dynamic Risk Assessment for Offender Re-entry. *M* = Mean. *SD* = Standard deviation.

Additionally, as illustrated by Table 5, a correlation matrix was conducted to examine the relationship between all DRAOR derived indicator variables. Results indicated no potential issues with multicollinearity as no pair of variables demonstrated large or near-perfect relationships. The majority of variables were found to be negligibly ($r < .30$) to weakly ($.30 > r < .50$) correlated, while 28 domains were found to be moderately ($.50 > r < .72$) correlated. The strongest correlations were found between social support and social control $r(1, 510) = .72$, $p < .001$ and between impulse control and problem solving $r(1,510) = .64$, $p < .001$.

Table 5

Correlation Matrix of DRAOR [a] Derived Indicator Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1. Peer associations	1	.52	.49	.49	.29	.39	.49	.37	.21	.32	.38	.29	.42	-.52	-.60	-.51	-.52	-.51	-.57
2. Attitudes toward authority		1	.53	.51	.55	.50	.36	.49	.18	.41	.28	.28	.33	-.55	-.47	-.45	-.47	-.36	-.40
3. Impulse control			1	.64	.40	.47	.41	.47	.30	.44	.24	.31	.25	-.44	-.53	-.39	-.49	-.29	-.35
4. Problem-solving				1	.35	.38	.37	.43	.22	.42	.33	.32	.29	-.48	-.51	-.46	-.53	-.37	-.41
5. Sense of entitlement					1	.49	.20	.45	.23	.25	.14	.22	.17	-.38	-.30	-.23	-.34	-.16	-.19
6. Attachment with others						1	.25	.50	.32	.35	.18	.34	.33	-.36	-.39	-.32	-.35	-.31	-.30
7. Substance abuse							1	.34	.13	.28	.18	.12	.23	-.37	-.40	-.33	-.41	-.30	-.33
8. Anger/hostility								1	.35	.37	.14	.35	.26	-.33	-.33	-.29	-.36	-.20	-.25
9. Opportunity/access to victims									1	.15	.08	.22	.15	-.18	-.22	-.13	-.17	-.15	-.13
10. Negative mood										1	.22	.28	.24	-.33	-.35	-.31	-.33	-.19	-.21
11. Employment											1	.23	.40	-.29	-.36	-.36	-.35	-.35	-.40
12. Interpersonal relationships												1	.35	-.2	-.36	-.32	-.31	-.25	-.33
13. Living situation													1	-.3	-.38	-.38	-.37	-.42	-.4
14. Responsiveness to advice														1	.55	.48	.57	.47	.50
15. Prosocial identity															1	.58	.61	.48	.56
16. Realistic high expectations																1	.56	.54	.52
17. Costs/benefits of staying crime-free																	1	.50	.57
18. Social support																		1	.72
19. Social control																			1

Note. [a] DRAOR = Dynamic Risk Assessment for Offender Re-entry

Main Analyses

Research Question One: Latent Class Analysis

Class Enumeration. LCA was used to elucidate subclasses of justice-involved males from the 19 DRAOR indicator variables and the covariate IRA score. The analysis was conducted using Mplus Version 8.5 (Muthén & Muthén, 1998-2017). To determine the number of classes to retain, a one, two, three, four, five, and six-class class solution were run incrementally to identify the best fitting model. In addition to considering prior theory and the parsimony and interpretability (i.e., the simplicity and substantive meaning of the latent classes) of the final solution, several fit indices were evaluated for the class enumeration process. Specifically, three information criteria (IC), including the AIC, BIC, and ABIC and two likelihood ratio tests, the LMR and the BLRT.

For the AIC, BIC, and ABIC lower values indicate a better model fit, for the LMR and BLRT a significant *p*-value is indicative of the more parsimonious model, determining when additional classes are no longer improving the fit or discrimination of the model (Ferguson et al., 2020; Nylund et al., 2007). To assess the quality of the classification in terms of how well each LCA solution partitioned the data into classes, entropy was consulted. Entropy values of .80 or higher are indicative of increased classification accuracy (Tein et al., 2013).

Table 6 shows the fit indices for the estimated models for the justice-involved males. The AIC and ABIC values continuously decreased across all six classes, however, the lowest value of the BIC corresponded to the five-class model. Additionally, the LMR test was significant at $p < .05$ for the two, three, four, and five-class solution, however, the LMR test was not significant for the six-class solution. The BLRT was significant across all class solutions. Finally, the five-class

solution had an entropy value of .93 which indicated a high separation level between the latent classes.

Overall, the BIC, LMR, and entropy indicated that a five-class model was preferred. Moreover, a five-class model was more parsimonious and simpler to interpret when compared to a six-class solution and was also in agreement with previous research focusing on the distribution of risk and need for justice-involved males (which suggest a three to five class/profile model for males; Piquero, 2008; Wanamaker, 2020; Wagstaff, 2020). Therefore, the five-class solution was determined to be the appropriate model and best fit the data.

Table 6

Fit Indices for LCA Model with 1-6 Classes

Class solution	AIC	BIC	ABIC	LMR (*p*)	BLRT	Entropy
1 - Class	21305.182	21474.558	21347.592	-	-	-
2 - Class	15599.526	15929.810	15682.227	0.0000	.0000	0.926
3 - Class	14822.716	15322.376	14947.828	0.0038	.0000	0.920
4 - Class	14364.986	15034.023	14532.509	0.0023	.0000	0.925
5 - Class	**14172.304**	**15010.717[a]**	**14382.237**	**0.0001[a]**	**.0000**	**0.932[a]**
6 - Class	14112.185[a]	15119.975	14364.530[a]	0.5422	.0000	0.928

Note. AIC = Akaike's Information Criterion. BIC = Bayesian Information Criteria. ABIC = Sample size adjusted Bayesian Information Criteria. BLRT = Bootstrap Likelihood Ratio Test LMR = Lo-Mendell-Rubin Likelihood ratio test. [a] Best fitting model according to that criterion. Bolded values indicate the chosen model.

Posterior Class Membership Probabilities. The next stage of the analysis involved examining the posterior probabilities. The posterior probabilities of class membership are estimated values of the probability that an individual is correctly identified as belonging to the class to which they have been assigned (Clark et al., 2013). Values equal to or greater than .70

are considered acceptable. As illustrated by Table 7, the posterior probabilities of class membership for the five-class solution ranged from .95 to .98. These probabilities of correct classification were considered acceptable and supported the retention of a five-class solution.

Table 7

Posterior Class Membership Probabilities for a Five-Class Structure

Most likely class membership	Latent Classes				
	1	2	3	4	5
1	**0.964**	0.000	0.000	0.000	0.036
2	0.000	**0.976**	0.021	0.000	0.003
3	0.000	0.015	**0.953**	0.001	0.031
4	0.000	0.000	0.002	**0.958**	0.040
5	0.012	0.004	0.031	0.008	**0.945**

Note. Probability of class membership classification equal to or greater than .70 is considered acceptable.

Probability Parameters. To define and label each of the five classes, the class probability parameters and the item parameters were examined (Table 8). The class probability parameters indicate the number of individuals belonging to each class (Nylund et al., 2007). The item parameters correspond to the conditional item probabilities or the probability that an individual in a given class would select a specific response on a specific item; these response patterns aided in distinguishing the classes (Nylund et al., 2007; Porcu & Giambona, 2012). Overall, class one contained 16.9% (n = 86) of the sample, class two contained 19.2% (n = 98), class three contained 23.5% (n = 120), class four contained 7% (n = 37), and class five contained 33% (n = 169) of the sample. See Figures 2, 3, and 4 for a graphical representation of the item response probabilities for the classes on each of the stable dynamic risk items, acute dynamic risk items, and protective items, respectively.

Table 8

Item Response Probabilities

DRAOR indicator items	Values	LC1 (*n* = 86)	LC2 (*n* = 98)	LC3 (*n* = 120)	LC4 (*n* = 37)	LC5 (*n* = 169)
Stable risk						
Peer associations	0[a]	0.708	0.000	0.000	0.027	0.120
	1[b]	0.292	0.364	0.951	0.973	0.863
	2[c]	0.000	0.636	0.049	0.000	0.018
Attitudes towards authority	0[a]	0.958	0.052	0.006	0.690	0.572
	1[b]	0.042	0.621	0.943	0.283	0.428
	2[c]	0.000	0.327	0.051	0.027	0.000
Impulse control	0[a]	0.722	0.000	0.000	0.527	0.233
	1[b]	0.266	0.340	0.904	0.473	0.679
	2[c]	0.011	0.660	0.096	0.000	0.089
Problem solving	0[a]	0.794	0.009	0.017	0.290	0.213
	1[b]	0.206	0.446	0.939	0.710	0.743
	2[c]	0.000	0.545	0.045	0.000	0.044
Sense of entitlement	0[a]	0.803	0.199	0.074	0.790	0.575
	1[b]	0.175	0.576	0.871	0.156	0.376
	2[c]	0.023	0.225	0.056	0.054	0.050
Attachment with others	0[a]	0.760	0.083	0.028	0.800	0.493
	1[b]	0.229	0.723	0.972	0.173	0.495
	2[c]	0.011	0.194	0.000	0.027	0.012
Acute risk						
Substance abuse	0[a]	0.899	0.126	0.175	0.463	0.480
	1[b]	0.079	0.347	0.646	0.537	0.347
	2[c]	0.022	0.527	0.179	0.000	0.173
Anger/hostility	0[a]	0.904	0.170	0.144	0.866	0.610
	1[b]	0.085	0.500	0.814	0.134	0.304
	2[c]	0.011	0.330	0.042	0.000	0.086
Opportunity/access to victims	0 [a]	0.585	0.286	0.157	0.902	0.459
	1 [b]	0.403	0.497	0.732	0.098	0.442
	2 [c]	0.011	0.217	0.111	0.000	0.099

DRAOR indicator items	Values	LC1 (*n* = 86)	LC2 (*n* = 98)	LC3 (*n* = 120)	LC4 (*n* = 37)	LC5 (*n* = 169)
Negative mood	0 [a]	0.767	0.138	0.136	0.713	0.525
	1 [b]	0.212	0.570	0.810	0.287	0.386
	2 [c]	0.021	0.293	0.054	0.000	0.089
Employment	0 [a]	0.834	0.177	0.280	0.000	0.559
	1 [b]	0.112	0.272	0.422	0.372	0.224
	2 [c]	0.054	0.551	0.298	0.628	0.217
Interpersonal relationships	0 [a]	0.583	0.025	0.102	0.168	0.303
	1 [b]	0.370	0.617	0.808	0.773	0.537
	2 [c]	0.047	0.359	0.090	0.059	0.159
Living situation	0 [a]	0.729	0.132	0.064	0.081	0.430
	1 [b]	0.260	0.519	0.811	0.751	0.494
	2 [c]	0.012	0.348	0.125	0.168	0.076
Protective factors						
Responsiveness to advice	0 [d]	0.000	0.352	0.041	0.027	0.022
	1 [e]	0.135	0.648	0.934	0.912	0.675
	2 [f]	0.865	0.000	0.024	0.061	0.303
Prosocial identity	0 [d]	0.000	0.503	0.015	0.054	0.006
	1 [e]	0.176	0.497	0.957	0.946	0.859
	2 [f]	0.824	0.000	0.028	0.000	0.135
Realistic high expectations	0 [d]	0.000	0.567	0.060	0.093	0.053
	1 [e]	0.106	0.396	0.850	0.907	0.607
	2 [f]	0.894	0.037	0.090	0.000	0.341
Costs/benefits	0 [d]	0.000	0.466	0.040	0.135	0.010
	1 [e]	0.059	0.534	0.939	0.839	0.728
	2 [f]	0.941	0.000	0.021	0.027	0.262
Social support	0 [d]	0.000	0.405	0.020	0.588	0.007
	1 [e]	0.166	0.553	0.937	0.412	0.609
	2 [f]	0.834	0.042	0.043	0.000	0.384
Social control	0 [d]	0.011	0.625	0.000	0.778	0.035
	1 [e]	0.265	0.375	1.000	0.222	0.830
	2 [f]	0.724	0.000	0.000	0.000	0.135
Overall	-	0.169	0.192	0.235	0.073	0.331

Note. [a] = Not a problem. [b] = Slight problem. [c] = Definite problem. [d] = Not an asset. [e] = Slight asset. [f] = Definite asset.

Description of the Latent Classes.

Latent Class One (n = 86, 16.9% of sample). Latent class one was best described as the *low dynamic risk/high protective* class. This class was defined by having higher probabilities of receiving a score of zero (i.e., not a problem) across all stable and acute dynamic risk factors, suggesting an overall classification of being low in dynamic risk. Furthermore, the individuals in this class had higher probabilities of receiving a score of two (i.e., definite asset) across all protective items, indicating that these individuals had several factors that supported their desistance from crime. Overall, this class represented the lowest risk class, as those in this class did not display difficulties in any of the dynamic risk or protective items.

Latent Class Two (n = 98, 19.2% of sample). Latent class two was best described as a *moderate to high dynamic risk/moderate to high protective* class, henceforth known as the c*omplex dynamic risk/complex protective* class[2]. This class was defined by having higher probabilities of receiving a score of two (i.e., definite problem) compared to a one (i.e., slight problem) for the stable dynamic risk items of peer associations, impulse control, and problem solving. Also, those in this class had higher probabilities of receiving a score of one (i.e., slight problem) for the stable dynamic risk items of attitudes toward authority, sense of entitlement, and attachment with others. When considering the acute risk items, those in this class had higher probabilities of receiving a score of two (i.e., definite problem) compared to one (i.e., slight problem) for the acute dynamic risk items of substance abuse and employment and a score of one (i.e., slight problem) for anger/hostility, opportunity/access to victims, negative mood, interpersonal relationships, and living situation. In general, the conditional item probabilities of

[2] The decision to refer to this class as *complex dynamic risk/complex protective* was made due to table formatting issues associated with longer labels.

having a score of two (i.e., definite problem) on the dynamic risk items were consistently higher for class two than for any other class, the only exception being employment, which was slightly higher for class four.

For the protective items, this class had higher probabilities of receiving a score of zero (i.e., not an asset) compared to a score of one (i.e., slight asset), for the items of prosocial identity, realistic high expectations, and social control. Additionally, this class had a higher probability of receiving a score of one (i.e., slight asset) for the remaining protective items. In general, the conditional probabilities of having a score of zero (i.e., not an asset) on the protective items were higher for class two than all other classes, apart from social support and social control. Overall, this class appeared to have the most difficulties, with higher probabilities of receiving higher scores on dynamic risk items and lower scores for protective items.

Latent Class Three (n = 120, 23.5% of sample). Latent class three was described as the *moderate dynamic risk/moderate protective* class. This class was defined by having the highest probabilities of receiving a score of one (i.e., slight problem) across all dynamic risk factors, apart from peer associations. Additionally, the individuals in this class had the highest probabilities of receiving a score of one (i.e., slight asset) across all protective items, apart from realistic high expectations. This class was considered to represent an overall moderate risk class, due to the higher probabilities of receiving a score of one across all DRAOR items.

Latent Class Four (n = 37, 7% of sample). Latent class four was labelled the *problematic employment/insufficient social support* class. Those in this class had the highest probability of receiving a score of two (i.e., definite problem) in only one risk factor: employment. For all other dynamic items, these individuals had higher probabilities of receiving a score of one (i.e., slight problem; peer associations, problem solving, substance abuse,

interpersonal relationships, living situation) or zero (i.e., not a problem; attitudes towards authority, impulse control, sense of entitlement, attachment to others, anger/hostility, opportunity/access to victims, and negative mood). This class was also defined by having higher probabilities of receiving a score of zero (i.e., not an asset) in the protective items of social support and social control. In all other protective items, those in this class had higher probabilities of receiving a score of one (i.e., slight asset). This class was the smallest, representing only 7% (n = 37) of the sample. Overall, those within this class were characterized by increased difficulties with employment and securing adequate social support.

Latent Class Five (n = 169, 33% of sample). Latent class five was best described as the *low to moderate dynamic risk/moderate protective* class, henceforth referred to as the *low-mod dynamic risk/mod protective* class[3]. This class was defined by having higher probabilities of receiving a score of zero (i.e., not a problem) across seven of the dynamic risk factors including, attitudes towards authority, sense of entitlement, substance abuse, anger/hostility, opportunity/access to victims, negative mood, and employment. Additionally, this class had higher probabilities of receiving a score of one (i.e., slight problem) across the six remaining dynamic risk items, including peer associations, impulse control, problem solving, attachment to others, interpersonal relationships, and living situation. Further, those in this class had higher probabilities of being assigned a score of 1 (i.e., slight asset) on all protective factors, with very low probabilities of receiving a score of zero (i.e., not an asset). Overall, this class was the largest class, representing 33% (n = 169) of the sample and was designated as a low to moderate risk class, only demonstrating slight needs in six of the 13 dynamic risk areas.

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[3] The decision to refer to this class as *low-mod dynamic risk/ mod protective* was made due to table formatting issues associated with longer labels.

Figure 2

Item Response Probabilities for the Six Stable Dynamic Risk Items

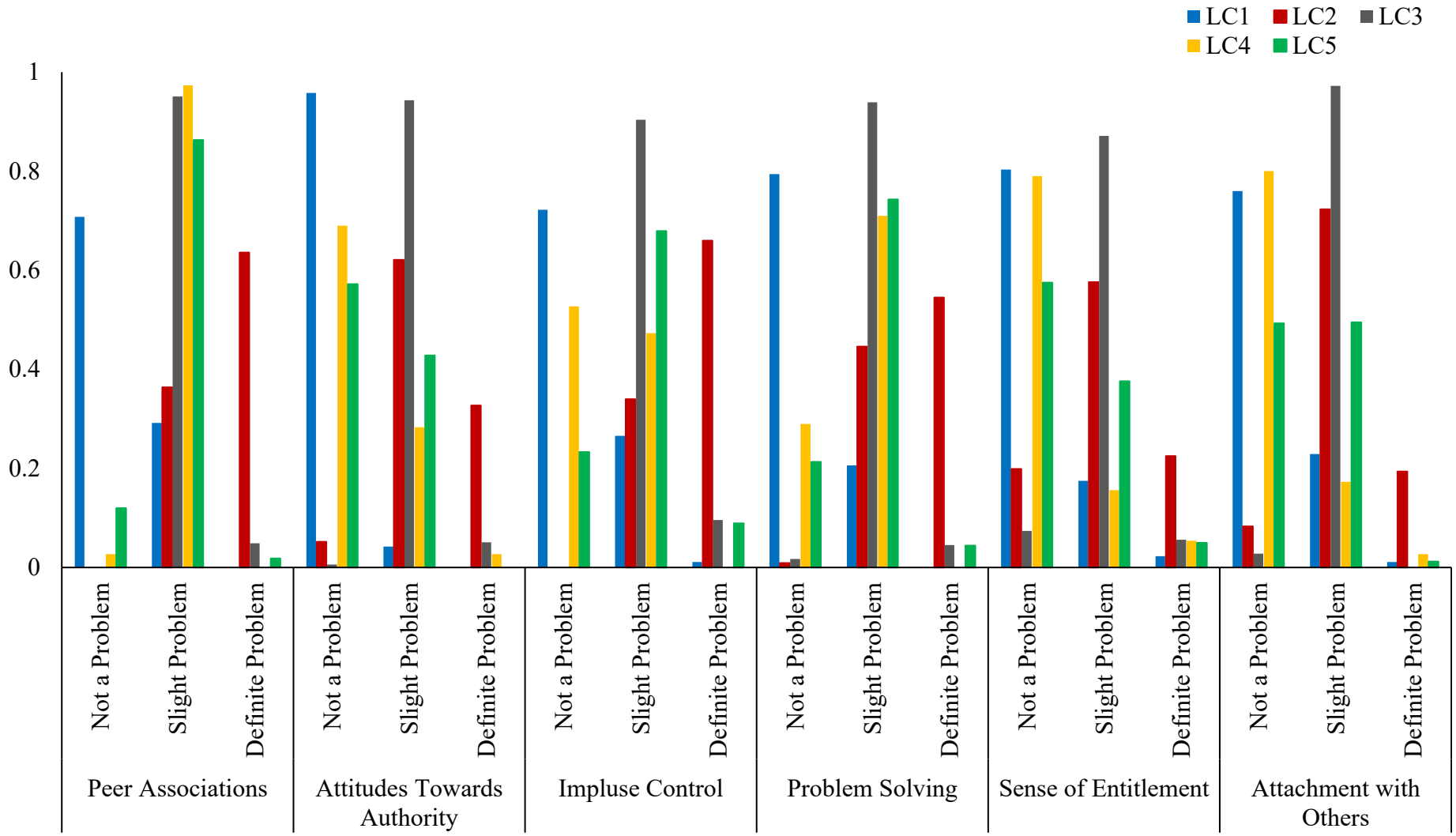


Figure 3

Item Response Probabilities for the Seven Acute Dynamic Risk Items

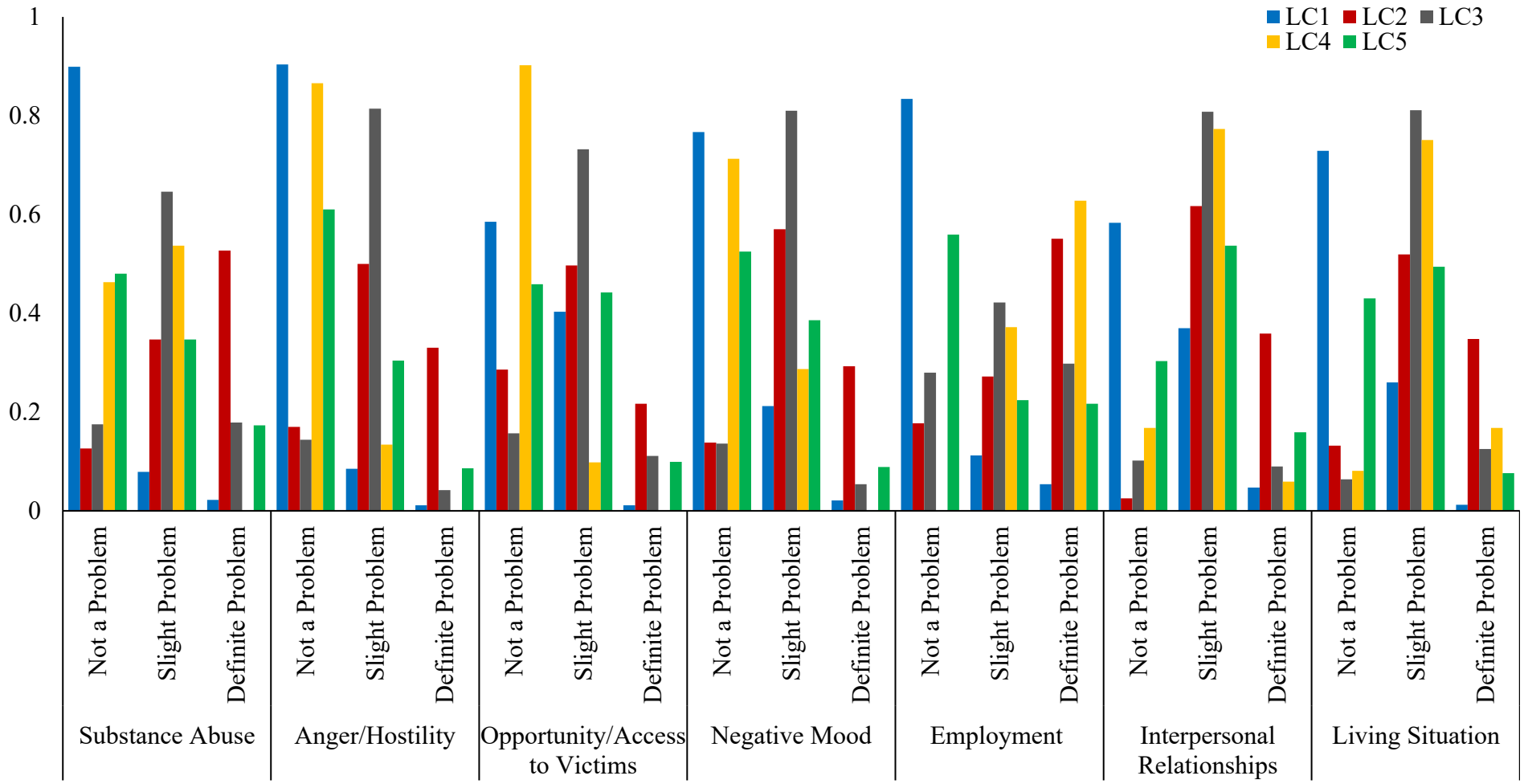
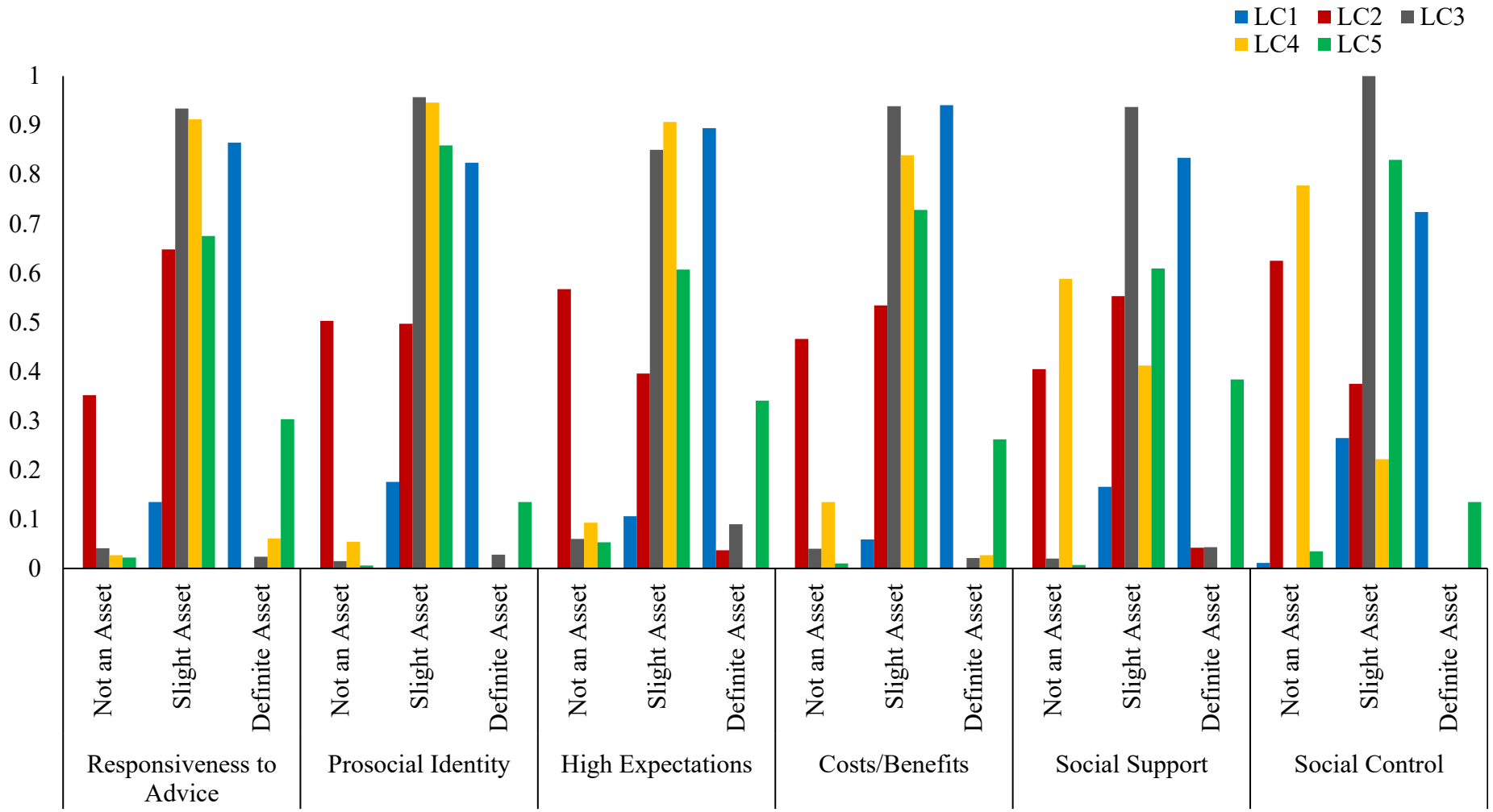


Figure 4

Item Response Probabilities for the Six Protective Items.



Research Question Two: Impact of IRA Static Risk Score on Class Enumeration

A one-way analysis of variance (ANOVA) was conducted to examine the impact of IRA static risk scores on class membership (Table 9). The IRA scores were included in the analysis as a covariate and controlled for during the class enumeration process. When covariates are included in the LCA, the effect of the covariate on the probability of an individual belonging to a certain latent class is examined (Porcu & Giambona, 2017). This can improve classification accuracy (Lubke & Muthén, 2007).

Results demonstrated a significant relationship between IRA static risk scores and class membership. The IRA static risk scores appeared to be the lowest for the *low dynamic risk/high protective* class and the highest for the *complex dynamic risk/complex protective* class and the *moderate dynamic risk/moderate protective* class.

Table 9

Means of the IRA [a] scores for Each Class

Classes	*n*	*M*	*SD*	*F*
Low [dr]/High [pr]	86	7.60	6.821	
Complex [dr]/Complex [pr]	98	15.20	4.951	
Moderate [dr]/Moderate [pr]	120	15.34	3.942	30.101***
Problematic [emp]/Insufficient [ss]	37	9.81	8.981	
Low-Mod [dr]/Mod [pr]	169	12.40	5.835	

Note. [a] IRA = Iowa Risk Assessment. *M* = Mean, *SD* = Standard deviation. *F* = Analysis of Variance (ANOVA). [dr] = Dynamic risk. [pr] = Protective. [emp] = Employment. [ss] = Social support. $^{*}p < .05$. $^{**}p < 01$. $^{***}p < .001$.

A multinomial logistic regression was further conducted to examine the relationships between each class. As depicted in Table 10, the overall model was significant ($X^2 = 103.58$, $p < .001$), demonstrating that the IRA static risk scores differed across the classes. All possible

pairwise comparisons between classes were examined, with each class separately acting as the reference group. There were significant differences in IRA scores between the five classes. However, the *problematic employment/insufficient social support* class was not significantly different in IRA static risk scores when compared to the *low dynamic risk/high protective class.* Additionally, the *moderate dynamic risk/moderate protective* class was not significantly different from the *complex dynamic risk/complex protective* class.

Table 10

Multinomial Logistic Regression of Classes on IRA [a] Static Risk Scores

Class	Odds Ratio	*SE*	*p*	[95% CI]
Reference: Low [dr]/High [pr]				
Complex [dr]/Complex [pr]	1.24	.030	.000***	[1.17, 1.31]
Moderate [dr]/Moderate [pr]	1.24	.029	.000***	[1.78, 1.32]
Problematic [emp]/Insufficient [ss]	1.04	.028	.131[ns]	[.99, 1.10]
Low-Mod [dr]/Mod [pr]	1.11	.021	.000***	[1.07, 1.16]
Reference: Complex [dr]/Complex [pr]				
Low [dr]/High [pr]	.81	.020	.000***	[.76, .86]
Moderate [dr]/Moderate [pr]	1.01	.030	.821[ns]	[.95, 1.07]
Problematic [emp]/Insufficient [ss]	.85	.034	.012*	[.79, .90]
Low-Mod [dr]/Mod [pr]	.90	.027	.000***	[.85, .95]
Reference: Moderate [dr]/Moderate [pr]				
Low [dr]/High [pr]	.80	.029	.000***	[.76, .85]
Complex [dr]/Complex [pr]	.99	.030	.821[ns]	[.94, 1.05]
Problematic [emp]/Insufficient [ss]	.84	.033	.000***	[.79, .90]
Low-Mod [dr]/Mod [pr]	.89	.026	.000***	[.85, .94]
Reference: Problematic [emp]/Insufficient [ss]				
Low [dr]/High [pr]	.96	.028	.131[ns]	[.91, 1.01]
Complex [dr]/Complex [pr]	1.18	.034	.000***	[1.12, 1.27]
Mod [dr]/Mod [pr]	1.19	.033	.000***	[1.12, 1.27]
Low-Moderate [dr]/Moderate [pr]	1.07	.027	.022*	[1.01, 1.12]
Reference: Low-Mod [dr]/Mod [pr]				
Low [dr]/High [pr]	.90	.021	.000***	[.87, .94]
Complex [dr]/Complex [pr]	1.11	.027	.000***	[1.06, 1.17]
Moderate [dr]/Moderate [pr]	1.12	.026	.000***	[1.07, 1.18]
Problematic [emp]/Insufficient [ss]	.94	.027	.022*	[.89, .99]
Overall Model: *-2 LL* [b] = 368.79 X^2 = 103.58 *df* = 4 *p* = .000***				

Note: [a] Iowa Risk Assessment. [b] Log Likelihood. SE = Standard Error. CI = confidence interval. X^2 = chi-square statistic. *df* = degrees of freedom. [dr] = Dynamic risk. [pr] = Protective. [emp] = Employment. [ss] = Social support. * $p < .05$. ** $p < 01$. ***$p < .001$.

Research Question Three: Distribution of Age and Race by Class

The equality tests of means across classes using the BCH approach (Bolck et al. 2004; Vermunt, 2010) were examined to assess the distribution of age and class membership. The BCH approach is recommended when examining variables that are considered antecedent to the analysis to ensure that they do not impact class membership (Aparouhov & Muthén, 2015; Bakk

et al., 2013; No & Hong, 2018). As illustrated in Table 11, the justice-involved males' average age ranged from 27.19 to 38.99 across the five classes. The *moderate dynamic risk/moderate protective* class had the lowest average age and those in the *low dynamic risk/high protective* had the highest average age. The omnibus chi-square test showed a significant difference in age across the classes (χ^2 (4, 510) = 16.88, $p < .001$).

Table 11

Mean Age for Justice-Involved Males by Class

Class	*n*	*M*	*SE*	χ^2	*p*
Low ^{dr}/High ^{pr}	86	38.99	1.36		
Complex ^{dr}/Complex ^{pr}	98	30.44	1.11		
Moderate ^{dr}/Moderate ^{pr}	120	27.19	1.04	52.70	0.000***
Problematic ^{emp}/Insufficient ^{ss}	37	33.09	2.27		
Low-Mod ^{dr}/Mod ^{pr}	169	33.41	0.97		

Note: M = Mean. SE = Standard Error. χ2 = chi-square. dr = Dynamic risk. pr = Protective. emp = Employment. ss = Social support. * $p < .05$. ** $p < 01$. ***$p < .001$.

The pairwise comparisons of age across classes were further examined (Table 12) and significant differences were found between classes. The *low dynamic risk/high protective* class was significantly different from all other classes, suggesting that those within the *low dynamic risk/high protective* class tended to be older than those in each of the other four groups. *The moderate dynamic risk/moderate protective* class also significantly differed from all other classes, suggesting that those within this class were significantly younger when compared to each of the other four groups. The *complex dynamic risk/complex protective* class was significantly different from the *low-mod dynamic risk/mod protective* class, suggesting that the latter group was older than the former. However, the *problematic employment/insufficient social support* class was not significantly different from the *complex dynamic risk/complex protective* or the *low-mod dynamic risk/mod protective* class.

Table 12

Comparisons of Age Across Classes

Class Comparisons	χ^2	*p*
Low ^{dr}/High ^{pr} vs. Complex ^{dr}/Complex ^{pr}	23.871	.000***
Low ^{dr}/High ^{pr} vs. Moderate ^{dr}/Moderate ^{pr}	47.768	.000***
Low ^{dr}/High ^{pr} vs. Problematic ^{emp}/Insufficient ^{ss}	4.992	.025*
Low ^{dr}/High ^{pr} vs. Low-Mod ^{dr}/Mod ^{pr}	10.760	.001***
Complex ^{dr}/Complex ^{pr} vs. Moderate ^{dr}/Moderate ^{pr}	4.417	.036*
Complex ^{dr}/Complex ^{pr} vs. Problematic ^{emp}/Insufficient ^{ss}	1.102	.294^{ns}
Complex ^{dr}/Complex ^{pr} vs. Low-Mod ^{dr}/Mod ^{pr}	4.082	.043*
Moderate ^{dr}/Moderate ^{pr} vs. Problematic ^{emp}/Insufficient ^{ss}	5.579	.018**
Moderate ^{dr}/Moderate ^{pr} vs. Low-Mod ^{dr}/Mod ^{pr}	18.034	.000***
Problematic ^{emp}/Insufficient ^{ss} vs. Low-Mod ^{dr}/Mod ^{pr}	.017	.896^{ns}

Note: χ^2 = chi-square. ^{ns} = not significant. ^{dr} = Dynamic risk. ^{pr} = Protective. ^{emp} = Employment. ^{ss} = Social support. $^{*}p < .05$. $^{**}p < 01$. $^{***}p < .001$

To explore how race was distributed across the classes, the equality tests of means across classes using the BCH procedure were examined; the means were equivalent to the proportion of those who identified as White. As depicted in Table 13, the omnibus chi-square test demonstrated a significant difference in race across the classes (χ^2 (4, 510) = 16.88, $p < .01$). Overall, when examining the descriptive statistics, there were higher percentages of those who identified as White across all classes, compared to those who identified as POC. Moreover, when specifically examining the proportion of each race across class, it appeared that those who identified as White were more likely to be categorized in the *low dynamic risk/high protective* class and those who identified as POC were more likely to be categorized in the *problematic employment/insufficient social support* class.

Table 13

Proportions of Race Distribution for Justice-Involved Males by Class

Class	*N*	White % (*n*)	POC[a] % (*n*)	χ^2	*p*
Low [dr]/High [pr]	86	82.6 (71)	17.4 (15)		
Complex [dr]/Complex [pr]	98	61.2 (60)	38.8 (38)		
Moderate [dr]/Moderate [pr]	120	70.8 (85)	29.2 (35)	16.88	0.002**
Problematic [emp]/Insufficient [ss]	37	54.1 (20)	45.9 (17)		
Low-Mod [dr]/Mod [pr]	169	74.6 (126)	25.4 (43)		
Total	510	71.0 (362)	29.0 (148)		

Note: χ^2 = chi-square. [ns] = not significant. [dr] = Dynamic risk. [pr] = Protective. [emp] = Employment. [ss] = Social support. * $p < .05$. ** $p < 01$. ***$p < .001$.

As illustrated in Table 14 all possible pairwise comparisons were examined for racial distribution across classes. There were significant differences between the *low dynamic risk/high protective* class and the *complex dynamic risk/complex protective* class (χ^2 (4, 510) = 11.03, $p <$ .01), the *moderate dynamic risk/moderate protective* class (χ^2 (4, 510) = 3.81, $p < .05$), and the *problematic employment/insufficient social support* class (χ^2 (4, 510) = 9.65, $p < .01$). However, the *low dynamic risk/high protective* class was not significantly different from the *low-mod dynamic risk/mod protective* class in terms of racial distribution.

The *complex dynamic risk/complex protective class* was also significantly different from the *low-mod dynamic risk/mod protective* class (χ^2 (4, 510) = 4.942, $p < .05$), but was not significantly different in racial distribution from the *moderate dynamic risk/moderate protective* class or the *problematic employment/insufficient social support* class. Furthermore, the *problematic employment/insufficient social support* class was significantly different in racial distribution from the *low-mod dynamic risk/mod protective* class (χ^2 (4, 510) = 5.263, $p < .05$). However, the *moderate dynamic risk/moderate protective* class was not significantly different

from the *problematic employment/Insufficient social support* class or the *low-mod dynamic risk/mod protective* class regarding racial distribution.

Table 14

Comparisons of Racial Distribution Across Classes

Class Comparisons	χ^2	*p*
Low ^{dr}/High ^{pr} vs. Complex ^{dr}/Complex ^{pr}	11.027	0.001^{**}
Low ^{dr}/High ^{pr} vs. Moderate ^{dr}/Moderate ^{pr}	3.813	0.051^{*}
Low ^{dr}/High ^{pr} vs. Problematic ^{emp}/Insufficient ^{ss}	9.653	0.002^{**}
Low ^{dr}/High ^{pr} vs. Low-Moderate ^{dr}/Moderate ^{pr}	2.061	0.151^{ns}
Complex ^{dr}/Complex ^{pr} vs. Moderate ^{dr}/Moderate ^{pr}	2.091	0.148^{ns}
Complex ^{dr}/Complex ^{pr} vs. Problematic ^{emp}/Insufficient ^{ss}	0.601	0.438^{ns}
Complex ^{dr}/Complex ^{pr} vs. Low-Mod ^{dr}/Mod ^{pr}	4.942	0.026^{*}
Moderate ^{dr}/Moderate ^{pr} vs. Problematic ^{emp}/Insufficient ^{ss}	3.348	0.067^{ns}
Moderate ^{dr}/Moderate ^{pr} vs. Low-Mod ^{dr}/Mod ^{pr}	0.434	0.510^{ns}
Problematic ^{emp}/Insufficient ^{ss} vs. Low-Mod ^{dr}/Mod ^{pr}	5.263	0.022^{*}

Note: χ^2 = chi-square. ^{ns} = not significant. ^{dr} = Dynamic risk. ^{pr} = Protective. ^{emp} = Employment. ^{ss} = Social support. $^{*}p < .05$. $^{**}p < 01$. $^{***}p < .001$.

Research Question Four: Recidivism Outcomes and Class Membership

As depicted in Table 15 four chi-square tests of independence were conducted to assess the relationship between the five recidivism outcomes and class membership. The relationship between class membership and recidivism was significant across outcomes. Across all outcomes, the *low dynamic risk/ high protective* class appeared to have the lowest rates of recidivism. Interestingly, the *complex dynamic risk/complex* protective had the highest proportion of recidivism for *any negative outcome* and *any technical violation.* However, the *problematic employment/insufficient social support* class demonstrated the highest proportions of recidivism for the outcomes of *any new offence, any new non-violent offence,* and *any new violent offence.* The largest disparities in the proportion of recidivism across classes appeared to be for *any*

negative outcome and *any technical violation*, while the smallest disparity across classes was found for *any violent offence.*

Table 15

Relationship Between Class Membership and Recidivism Outcomes

	Any negative outcome	Any offence	Any non-violent offence	Any violent offence	Any technical violation
	% (*n*)	% (*n*)	% (*n*)	% (*n*)	% (*n*)
Overall Sample Base Rates	69.8 (356)	38 (194)	27.1 (138)	11 (56)	64.9 (331)
Low [dr]/High [pr] (*n* = 86)	30.2 (26)	18.6 (16)	16.3 (14)	2.3 (2)	25.6 (22)
Complex [dr]/Complex [pr] (*n* = 98)	86.7 (85)	40.8 (40)	27.6 (27)	13.3 (13)	83.7 (82)
Moderate [dr]/Moderate [pr] (*n* = 120)	83.3 (100)	45.8 (55)	31.7 (38)	14.2 (17)	75.8 (91)
Problematic [emp]/Insufficient [ss] (*n* = 37)	83.8 (31)	56.8 (21)	35.1 (13)	21.6 (8)	78.4 (29)
Low-Mod [dr]/Mod [pr] (*n* = 169)	67.5 (114)	36.7 (62)	27.2 (46)	9.5 (16)	63.3 (107)
χ^2	105.20***	29.31***	9.34*	22.45***	106.23***

Note: χ^2 = chi-square. [dr] = Dynamic risk. [pr] = Protective. [ss] = Social support. $^{*}p < .05$. $^{**}p < 01$. $^{***}p < .001$.

Pairwise comparisons were further conducted between classes for each of the recidivism outcomes (Table 16).

Any Negative Outcome (69.8%, *n* = 356 of the overall sample). For the distal outcome variable of *any negative outcome*, the *low dynamic risk/high protective* class was significantly different from all other classes. Additionally, the *low-mod dynamic risk/mod protective* class was significantly different from the *complex dynamic risk/complex protective* class, the *moderate dynamic risk/moderate protective* class, and the *problematic employment/insufficient social support class.* These results indicated that the *low dynamic risk/high protective* class had significantly fewer instances of recidivism when compared to the four other classes, followed by the *low-mod dynamic risk/mod protective* class. However, the *complex dynamic risk/complex protective* class*,* the *moderate dynamic risk/moderate protective risk* class and the *problematic employment/insufficient social support* class were not significantly different from each other. This indicated that these three classes had similar rates of recidivism compared to each other, but higher rates of recidivism when compared to the *low dynamic risk/high protective* class and the *low-mod dynamic risk/mod protective* class.

Any New Offence (38%, *n* = 194 of the overall sample). For the distal outcome variable of *any new offence,* the *low dynamic risk/high protective* class was significantly different from all other classes; suggesting that this class had the lowest rate of incurring a new criminal charge. Additionally, the *problematic employment/insufficient social support* class and the *low-mod dynamic risk/mod protective* class were significantly different from each other, with the *problematic employment/insufficient social support* class having a higher rate of new offences. However, the *complex dynamic risk/complex protective* class was not significantly different from any other class, bar the *low dynamic risk/high protective class.* And the *moderate*

dynamic risk/moderate protective class was not significantly different from the *problematic employment/insufficient social support* class or the *low-mod dynamic risk/mod protective* class, suggesting similar rates of incurring a new criminal charge.

Any New Non-violent Offence (27.1%, *n* = 138 of the overall sample). Pertaining to the distal outcome variable of *any new non-violent offence,* the *low dynamic risk/high protective* class was significantly different from the *complex dynamic risk/complex protective* class, the *moderate dynamic risk/moderate protective* class, the *problematic employment/insufficient social support* class, and the *low-mod dynamic risk/mod protective class.* No other classes were found to be significantly different from each other. This suggests that the *low dynamic risk/high protective* class had the lowest rate of incurring a new charge for a non-violent offence, while all other classes had similar rates.

Any New Violent Offence (11%, *n* = 56 of the overall sample). For *any violent offence*, the *low dynamic risk/high protective* class was significantly different from all other classes. However, the *complex dynamic risk/complex protective* class, the *moderate dynamic risk/moderate protective* class, the *problematic employment/insufficient social support* class, and the *low-mod dynamic risk/mod protective* class were not significantly different from each other. These results indicated that the *low dynamic risk/high protective* class had the lowest rate of incurring a new charge for a violent offence, while all other classes had similar rates.

Any Technical Violation (64.9%, *n* = 331 of the overall sample). Regarding the distal variable of *any technical violation,* the *low dynamic risk/high protective* class was significantly different from all other classes. This suggests that the *low dynamic risk/high protective* class had the lowest rate of conditional breaches while on community supervision. Additionally, significant differences were found for the *low-mod dynamic risk/mod protective* class between

the *complex dynamic risk/complex protective* class and the *moderate dynamic risk/moderate protective* class, indicating that the *low-mod dynamic risk/mod protective* class incurred significantly fewer technical violations compared to the latter two classes. However, the *complex dynamic risk/complex protective* class was not significantly different from the *moderate dynamic risk/moderate protective* class, indicating similar rates of incurring a technical violation. The *problematic employment/insufficient social support* class was not significantly different from any of the other classes bar the *low dynamic risk/high protective* class, implying similar rates of breaching a condition of community release across classes.

Table 16

Comparisons of Recidivism Outcomes by Class

	Any negative outcome		Any new offence		Any non-violent offence		Any violent offence		Any technical violation	
Class Comparisons	χ^2	*p*	χ^2	*p*	χ^2	*p*	χ^2	*p*	χ^2	*p*
Low ^{dr}/High ^{pr} vs. Complex ^{dr}/Complex ^{pr}	86.98	$.000^{***}$	11.45	$.001^{***}$	3.44	$.064^{***}$	8.16	$.004^{***}$	92.65	$.000^{***}$
Low ^{dr}/High ^{pr} vs. Moderate ^{dr}/Moderate ^{pr}	76.80	$.000^{***}$	18.89	$.000^{***}$	6.83	$.009^{**}$	10.48	$.001^{***}$	65.52	$.000^{***}$
Low ^{dr}/High ^{pr} vs. Problematic ^{emp}/Insufficient ^{ss}	46.32	$.000^{***}$	17.18	$.000^{***}$	4.54	$.033^{*}$	7.60	$.006^{**}$	40.49	$.000^{***}$
Low ^{dr}/High ^{pr} vs. Low-Mod ^{dr}/Moderate ^{pr}	34.95	$.000^{***}$	9.65	$.002^{**}$	4.07	$.044^{*}$	5.91	$.015^{*}$	37.66	$.000^{***}$
Complex ^{dr}/Complex ^{pr} vs. Moderate ^{dr}/Moderate ^{pr}	.32	$.571^{ns}$	.61	$.434^{ns}$	.46	$.500^{ns}$	.05	$.820^{ns}$	1.78	$.182^{ns}$
Complex^{dr}/Complex^{pr} vs. Problematic^{emp}/Insufficient^{ss}	.13	$.722^{ns}$	2.88	$.090^{ns}$	.72	$.400^{ns}$	1.26	$.263^{ns}$	.398	$.528^{ns}$
Complex ^{dr}/Complex ^{pr} vs. Low-Mod ^{dr}/Moderate ^{pr}	13.73	$.000^{***}$	.407	$.524^{ns}$	.00	$.970^{ns}$	.84	$.360^{ns}$	13.69	$.000^{***}$
Moderate^{dr}/Moderate^{pr} vs. Problematic^{emp}/Insufficient^{ss}	.002	$.962^{ns}$	1.31	$.253^{ns}$	.14	$.71^{ns}$	.97	$.326^{ns}$	.105	$.746^{ns}$
Moderate ^{dr}/Moderate ^{pr} vs. Low-Mod ^{dr}/Mod ^{pr}	9.02	$.003^{**}$	2.28	$.131^{ns}$	.61	$.433^{ns}$	1.38	$.240^{ns}$	4.57	$.032^{*}$
Problematic ^{emp}/Insufficient ^{ss} vs. Low-Mod ^{dr}/Mod ^{pr}	4.99	$.025^{*}$	4.88	$.027^{*}$	.82	$.366^{ns}$	2.86	$.09^{ns}$	3.51	$.061^{ns}$

Note: χ^2 = chi-square. ^{dr} = Dynamic risk. ^{pr} = Protective. ^{emp} = Employment. ^{ss} = Social support. * $p < .05$. ** $p < 01$. ***$p < .001$

Research Question Five: Predictive Validity of the DRAOR by Class, for Recidivism Outcomes

Total DRAOR Score. As illustrated by Table 17, a series of ROC analyses were performed to examine the predictive accuracy of the DRAOR total scores for each of the five binary recidivism outcomes: for the full sample and across the five classes. Pertaining to the overall sample, results indicated that the DRAOR total scores were able to discriminate between recidivists and non-recidivists with large levels of predictive accuracy for *any negative outcome* (AUC = .738) and *any technical violation* (AUC = .723). Results were less positive for the prediction of incurring a new charge while on supervision; AUC's yielded small to moderate levels of accuracy for *any new offence* (AUC = .587) and *any violent offence* (AUC = .627). The AUC for *any non-violent offence* was not significant (AUC = .541).

Class Membership. When assessing how the predictive validity of the DRAOR varied as a function of class membership, the majority of AUCs were not significant. However, the *low dynamic risk/high protective* class was moderately predictive of *any negative outcome*, *any new offence*, and *any new violent offence* (AUCs ranging from .663 to .694). This class also demonstrated a large level of predictive accuracy for any technical violation (AUC = .739). Further, the *moderate dynamic risk/moderate protective class* yielded a moderate level of predictive accuracy for *any technical violation* (AUC = .633). Notably, the *complex dynamic risk/complex protective* class demonstrated a moderate level of predictive accuracy for *any violent offence* (AUC = .649).

Table 17

Predictive Validity of the DRAOR Total Scores for Recidivism Outcomes of Justice-Involved Males

	Statistic	Any negative outcome	Any new offence	Any non-violent offence	Any violent offence	Any technical violation
Overall sample (N = 510)	AUC	.738***	.587***	.541^{ns}	.627**	.723***
	SE	.025	.025	.027	.035	.024
	[95% CI]	[.690, .786]	[.537, .636]	[.487, .594]	[.557, .697]	[.677, .770]
Low ^{dr}/High ^{pr} (n = 86)	AUC	.694**	.663*	.683*	.491^{ns}	.739***
	SE	.065	.077	.076	.261	.063
	[95% CI]	[.56, .822]	[.512, .814]	[.534, .831]	[.000, 1.000]	[.615, .862]
Complex ^{dr}/Complex ^{pr} (n = 98)	AUC	.628^{ns}	.596^{ns}	.517^{ns}	.671*	.649^{ns}
	SE	.089	.059	.065	.082	.076
	[95% CI]	[.454, .802]	[.480, .711]	[.390, .645]	[.510, .832]	[.500, .798]
Moderate ^{dr}/Moderate ^{pr} (n = 120)	AUC	.614^{ns}	.455^{ns}	.432^{ns}	.529^{ns}	.633*
	SE	.061	.053	.056	.076	.058
	[95% CI]	[.495, .734]	[.351, .559]	[.322, .542]	[.381, .677]	[.520, .746]
Problematic ^{emp}/Insufficient ^{ss} (n = 31)	AUC	.444^{ns}	.488^{ns}	.420^{ns}	.591^{ns}	.455^{ns}
	SE	.163	.102	.096	.103	.135
	[95% CI]	[.124, .763]	[.287, .689]	[.231, .608]	[.389, .792]	[.190, .719]
Low-Mod ^{dr}/Mod ^{pr} (n = 114)	AUC	.510^{ns}	.519^{ns}	.491^{ns}	.573^{ns}	.494^{ns}
	SE	.047	.046	.050	.075	.045
	[95% CI]	[.418 - .602]	[.428, .610]	[.393, .588]	[.427, .720]	[.405, .584]

Note. AUC values of .56, .64, and .71 represent small, moderate, and large effect sizes. SE = standard error. CI = confidence interval. ^{dr} = dynamic risk. ^{pr} = protective. ^{emp} = employment. ss = Social Support. * $p < .05$. ** $p < 01$. ***$p < .001$.

Further analyses were conducted to determine if there were significant statistical differences between the predictive accuracy of the classes and the predictive accuracy of the DRAOR total scores for the overall sample. Only AUCs that yielded significant results were compared. AUCs were compared using MedCalc version 19.8 (MedCalc Software Ltd., 2021), which allows for the comparison of AUC statistics using the method described by Hanley and McNeil (1983). For *any negative outcome*, the overall sample AUC (.738) was compared to the AUC score yielded by the *low dynamic/high protective* class (AUC =. 694), this comparison was not significant (z = .632, p = .5275). For *any new offence*, the overall sample AUC (.587) was compared to the AUC score yielded by the *low dynamic/high protective class* (AUC = .663), this comparison was not significant (z = .939, p = .3478). For *any technical violation,* the overall sample AUC (.723) was compared to the AUCs yielded by the *low dynamic risk/high protective* class (AUC = .739) and the *moderate dynamic risk/moderate protective class* (AUC = .633), neither of these comparisons were significant (z = .237, p = .8124 and z = 1.434, p = .1516, respectively).

Discussion

The purpose of the current study was to examine the utility of a person-centered approach to risk assessment. To accomplish this goal, an LCA was conducted using the DRAOR case management tool, which consists of 13 dynamic factors (six stable and seven acute) and six protective factors. The IRA, a measure of static risk, was entered into the analysis as a covariate and the demographic variables of age and race were examined as distal variables. In addition to detecting these latent groups, a secondary goal was to examine the relationship between the latent groups and recidivism outcomes in terms of frequency and predictive utility. These goals were addressed by answering the following five research questions: (1) Can meaningful

typologies be delineated among justice-involved males in Iowa, using dynamic and protective variables derived from the DRAOR? (2) Is class membership related to IRA static risk scores? (3) Is class membership related to the demographic variables of age and race? (4) Do recidivism rates vary as a function of class membership? and (5) a) Is the predictive validity of the DRAOR related to class membership, and b) does the predictive validity of the classes exceed that of the DRAOR total scores for the overall sample?

Summary of the Resultant Classes

The first research question examined whether meaningful typologies could be delineated among justice-involved males in Iowa utilizing variables derived from the DRAOR. A series of LCAs were examined during the class enumeration process. Five distinct classes were identified: (1) the *low dynamic risk/high protective class*, (2) the *complex dynamic risk/complex protective* class, (3) the *moderate dynamic risk/moderate protective* class, (4) the *problematic employment/insufficient social support* class and (5) the *low-mod dynamic risk/mod protective* class. Each demonstrated unique differences in their distribution of DRAOR item scores.

The *low dynamic risk/high protective* class received low scores across all dynamic risk items and high scores across all protective items. Individuals in this class tended to be older (M = 38.99) and identify as White (82.6%; n = 71). Additionally, this class demonstrated the lowest IRA static risk scores (M = 7.60). Within this class, the rate of engaging in any form of recidivism was (30.2%, n = 26). This class demonstrated the lowest rates of recidivism across all outcomes compared to the other classes.

The *complex dynamic risk/complex protective* class received moderate to high scores across the dynamic risk items, and low to moderate scores across the protective items. Those within this class were more likely to be White (61.2%; n = 60), however, this class included the

second-highest percentage of POC (38.8%; *n* = 38). This class was also identified by having the second highest IRA score (*M* = 15.20). Of the individuals within this class, 86.7% (*n* = 85) were identified as recidivists. Moreover, when compared to the other classes, the *complex dynamic risk/complex protective* class appeared to represent the highest risk class, with difficulties in multiple domains.

The *moderate dynamic risk/moderate protective* class received moderate scores across all dynamic and protective items. Those within this class were the youngest (*M* = 27.19), and the majority identified as White (70.8%; *n* = 85). Moreover, this class had the highest IRA scores (*M* = 15.34) and 83.3% (*n* = 31) of the individuals within this class were identified as recidivists. This class represented an overall moderate risk class.

The *problematic employment/insufficient social support* class was the smallest class (7%; *n* = 37) and was defined by low to moderate scores across most dynamic risk items, except for employment, in which they received high scores. Furthermore, this class received moderate scores across most protective items but were identified based on their low scores in social support and social control. Moreover, the majority of individuals within this class identified as White (54.1%; *n* = 20) however, this class included the highest percentage of POC (45.9%; *n* = 17). This class was also noted for their low IRA scores (*M* = 9.81), which while comparable to the *low dynamic risk/low protective* class, were significantly lower than all other classes. Additionally, the rate of engaging in any form of recidivism for this class was 83.8% (*n* = 31). Overall, in comparison to the other classes, this group had high needs in maintaining quality employment and fostering prosocial relationships.

Finally, the *low-mod dynamic risk/mod protective* class was the largest class (*n* = 169) and was defined by low to moderate scores across the dynamic risk factors and moderate scores

across all protective factors. Those within this class were more likely to identify as White (74.6%; *n* =126) and had IRA scores that fell in the middle range when compared to the other classes (*M* = 12.40). Of the individuals within this class, 67.5% (*n* = 114) were identified as engaging in recidivism.

As expected, several classes emerged, and the classification of justice-involved males extended beyond groupings of low, moderate, and high risk that are traditionally based on a numerical count of the presence or absence of a set of criminogenic needs. While an overall low risk class and an overall moderate risk class were identified (i.e., *the low dynamic risk/high protective* class and the *moderate dynamic risk/moderate protective* class), the remaining three classes varied in their identified levels of need.

Impact of the IRA Static Risk Scores on Class Membership

The second research question examined the relationship between IRA static risk scores and class membership. Consistent with the hypothesis, the IRA risk scores were found to significantly inform class membership. The *low dynamic risk/high protective* class yielded similar IRA scores to the *problematic employment/insufficient social support* class, with both classes representing the lowest IRA scores (*M* = 7.60, *M* = 9.81, respectively). The *low-mod dynamic risk/mod protective* class had IRA scores that were significantly different from all other classes, placing this class in the middle range (*M* = 12.40). Finally, the *moderate dynamic risk/moderate protective* class yielded similar IRA scores as the *complex dynamic risk/complex protective* class, with both classes representing the groups with the highest IRA scores (*M* = 15.34, *M* = 15.20, respectively).

Inconsistent with the hypothesis, the IRA static risk scores were unable to accurately classify all the justice-involved males into low, moderate, and high risk and protective

categories. Specifically, while the *low dynamic risk/low protective* class yielded low IRA scores, the *problematic employment/insufficient social support* class also yielded low IRA scores, despite their high score in the dynamic risk item of employment, their moderate scores across five other dynamic risk items (i.e., peer associations, problem solving, substance abuse, interpersonal relationships and living situation), and their moderate to low scores across protective factors. Further, while the *complex dynamic risk/complex protective* class was noted for having moderate to high scores across dynamic items and moderate to low scores across protective factors, this class was identified as having similar IRA scores to the *moderate dynamic risk/moderate protective* class, characterized by moderate scores across all dynamic and protective items. These findings supported the person-centered approach, as individuals were not linearly classified into low, moderate, and high-risk groups but varied in terms of static risk level, dynamic risk level, and protective factors.

The IRA is a measure of static risk and is comprised of 13 historical factors identified as being predictive of recidivism (e.g., number of prior convictions; Chadwick, 2014). Some scholars have suggested that the relevance of historical factors, such as criminal history, diminishes over time (e.g., Blumstein & Nakamura, 2009; Bushway et al. 2011; Serin, 2020). In contrast, when dynamic and protective factors are assessed (and reassessed), the scores reflect changes over time and provide a more holistic view of the individual's current propensity to reoffend. Serin (2020) coined the term "risk decay" to refer to the reduction in the predictive utility of static risk factors over time when individuals have remained "offence-free" for an extended period of time.

As previously mentioned, the length of time the justice-involved males were on community release at the time of the initial DRAOR assessment was varied, with the average

length on community release prior to being assessed being approximately one year. A large number of participants (56.7%) had been on community release for at least six months, prior to their DRAOR assessment. Notably, the stage immediately following release is considered the most challenging, with rates of recidivism and technical violations peaking within the first few months (Burnett, 2009). It is possible, that the length of time spent on conditional release, may have distorted the relevance of the historical factors and in turn affected how the IRA score was related to class membership. However, how long the individual must spend offence-free to witness static risk decay is unclear (see Flores et al., 2017), therefore future LCAs conducted with the DRAOR should consider potential changes in how static risk is related to class membership over time.

Relationship Between Age and Race on Class Membership

The third research question assessed whether the demographic variables of age and race were related to class membership. These variables were included as distal variables to ensure that they did not impact the formation of the classes (Marsh et al., 2009). Examining the relationship of demographic variables, such as age and race, to the classes can provide valuable information regarding certain groups and their corresponding levels of risk (Campbell et al., 2018).

Age.

Consistent with the hypothesis, the average ages were significantly different across classes. The *low dynamic risk/high protective* class was significantly older when compared to all other classes. Further, individuals within the *moderate dynamic risk/moderate protective* class were significantly younger than the other four classes. The other three classes, the *problematic employment/insufficient social support* class, the *complex dynamic risk/complex protective* class and the *low-mod dynamic risk/mod protective* class did not differ regarding age, falling somewhere in the middle of the former two classes.

These findings were in contrast with previous research that has not found any significant differences of age between typologies derived from risk, need, and strength factors (e.g., Wagstaff, 2020; Brown et al., 2020). However, the majority of studies assessing the distribution of age across typologies have been conducted with justice-involved adolescents, resulting in restricted age ranges. The present research however had a broad age range, with an acceptable distribution of ages (55.5% < age 30 > 44.5%). Additionally, given that the group identified as the lowest risk was the oldest, these results are in line with the age crime curve which suggests that individuals who become criminally involved at younger ages, experience a peak in offending behaviour, followed by a decline during adulthood (Loeber et al., 1991; Morizot & Kazemian, 2015) as reflected in the Transition Model of Offender Change (Serin et al., 2010).

Furthermore, if classes based on dynamic risk and protective factors do differ according to age, this may have broader implications for programming. Higley et al. (2019) expanded on the idea that age can be considered a specific responsivity factor of the RNR approach, meaning that while age is unlikely to be directly related to recidivism (non-criminogenic) or directly targeted in rehabilitation programs, age may impact the client's receptivity to programming. Higley et al. (2019) conducted a study with a sample of 2, 417 violent, justice-involved adult males in Canada, and found that younger participants had lower levels of program performance and higher likelihoods of recidivism when compared to older participants, regardless of risk level, when controlling for the effect of risk and higher age. Interestingly, older individuals presenting at program intake with similar levels of criminogenic need still performed better when compared to their younger counterparts. Overall, age appeared to be an important consideration when attempting to improve offender programming and in the context of recidivism prediction. Program evaluators should consider the relationship between age and receptivity, potentially

incorporating pre-program primers to engage and motivate younger justice-involved individuals prior to enrolling them within correctional programs.

Race.

Concerning the relationship between race and the resultant classes, given the mixed results of previous studies, and the overreliance on justice-involved adolescent populations, no specific hypothesis was stated. The distribution of race across class was examined in an exploratory fashion. Findings demonstrated that race was related to the resultant LCA classes.

Specifically, across all classes, there was a higher percentage of those who identified as White compared to those who identified as POC, notwithstanding unequal distribution in the current sample. When examining the proportions of each racial group, those who identified as White were more likely to be categorized within the classes identified as being lower in dynamic risk (i.e., the *low dynamic risk/high protective* class and *low-mod dynamic risk/mod protective* class). In contrast, those who identified as POC were more likely to be categorized within the *problematic employment/insufficient social support* class followed by the *complex dynamic risk/complex protective* class. While the *complex dynamic risk/complex protective* class demonstrated higher needs overall, both classes represented the highest probabilities for receiving a score of two (i.e., definite problem) in the acute dynamic risk item of employment. Additionally, both groups were likely to receive a score of zero (i.e., not an asset) or one (i.e., slight asset) across protective factors. These differences in racial representation across classes are problematic and may be indicative of wider systemic issues both within the correctional system and society.

Racial disparities in incarceration rates in Iowa are pervasive. In 2021, 64% of incarcerated individuals were White while approximately 37% identified as POC (26% Black; 7% Hispanic; 2% American Indian or Alaskan Native; 1% Asian or Pacific Islander; Iowa Department of

Corrections, n.d.). In comparison, within the general population in Iowa, 85% identify as White and approximately 15% identity as POC (6.3% Hispanic or Latino; 4.1% Black; 2.7% Asian; 2.0% two or more races; 0.5% American Indian and Alaska Native; 0.2% Native Hawaiian and Other Pacific Islander; U.S Census Bureau, n.d.).

In 2020, the Iowa Department of Corrections released a racial disparity report to examine racial differences throughout varying sectors of the correctional system. They found that while there was equal representation in areas such as work assignments and intervention programs, POC were more likely to be classified as higher risk, to be assigned to maximum security, to receive disciplinary violations, were overrepresented in administrative segregation, and were more likely to return to prison due to technical violations when compared to White individuals (Fineran, 2020). Overall, there is a clear overrepresentation of POC within the correctional population and additional disparities related to the treatment of justice-involved POC within the institutions. This disparity is concerning and may potentially indicate these overrepresented groups of individuals have varying criminogenic needs, exacerbated by wider systemic issues that need to be addressed.

Previous research has indicated that race is not a major concern when assessing risk (Skeem & Lowenkamp, 2016); while this may be the case when considering overall risk level, considerations of potential, unique criminogenic needs, should be further explored. Overall, the results of the present study trend toward identifying specific needs that impact POC, however, due to the unequal proportions of race within the present sample, it is difficult to discern whether these differences in item scores are meaningful. Nonetheless, program developers and correctional staff should be considerate of these disparities, address biases (both conscious and unconscious), and be knowledgeable about cultural differences to minimize inequalities within

the correctional system and ensure POC are provided with opportunities and programs dedicated to helping them succeed.

Relationship between Recidivism Outcomes and Class Membership

Research question four focused on the relationship between the five recidivism outcomes (*any negative outcome*, *any new offence*, *any new non-violent offence*, *any new violent offence*, and *any technical violation*). It was hypothesized that the relationship between recidivism rates would vary across classes. This hypothesis was partially supported.

Across all outcomes, the *low dynamic risk/high protective* class had the lowest rates of offending behaviour. The *low-mod dynamic risk/mod protective* class had the second-lowest rate engaging in any form of recidivism (i.e., new offences and technical violations) and had lower rates of incurring a new criminal charge (i.e., any new offence) when compared to the *problematic employment/insufficient social support* class. Furthermore, the *low-mod dynamic risk/mod protective* class incurred a lower rate of technical violations compared to the *complex dynamic risk/complex protective* class and the *moderate dynamic risk/moderate protective* class. However, there were no differences in the rate of technical violations between the *complex dynamic risk/complex protective* class, the *moderate dynamic risk/moderate protective* class and the *problematic employment/insufficient social support* class. Furthermore, the *low-mod dynamic risk/mod protective* class, the *moderate dynamic risk/moderate protective* class, the *problematic employment/insufficient social support* class, and the *complex dynamic risk/complex protective class* did not differ in recidivism rates for any new non-violent offence or any new violent offence.

The lack of variability in recidivism rates was surprising, although the *low dynamic risk/high protective class* did incur the lowest rates of recidivism, as expected; there was less

distinction between the other class. The *low-mod dynamic risk/mod protective* class, while also considered a "lower risk" class, was the second lowest for any negative outcome however, this was not replicated across the other outcomes. Additionally, while the *complex dynamic risk/complex protective* class represented the highest risk class and did have higher rates of recidivism when compared to the *low dynamic risk/high protective* class, this class demonstrated relatively similar rates of recidivism across the outcomes when compared to both the *moderate dynamic risk/moderate protective* class and the *problematic employment/insufficient social support* class.

Comparison of the Predictive Validity of the DRAOR Total Score and the Classes

The fifth research question addressed the predictive utility of the resultant classes. The DRAOR total scores of the overall sample were found to be predictive of all recidivism outcomes (AUCs = .587-.738), except for any new non-violent offence (AUC = .541). The *low dynamic risk/high protective* was found to predictive of all recidivism outcomes, apart from any violent offence (AUCs = .663 - .739). However, the *complex dynamic risk/complex protective* class was only predictive of any new violent offence (AUC = .671) and the *moderate dynamic risk/moderate protective* class was only predictive of technical violations (AUC = .633). Furthermore, the *problematic employment/insufficient social support* class and *low-mod dynamic risk/mod protective* class were not predictive of the recidivism outcomes (AUCs = .420 - .590), suggesting these classes were unable to predict recidivism better than chance. In the instances where the classes were predictive of recidivism outcomes, there were no significant differences between the DRAOR overall sample and class AUCs. Overall, the hypothesis was partially supported. The DRAOR overall sample scores and the *low dynamic risk/high protective* class were the most consistently predictive of the recidivism outcomes and yielded similar AUCs.

However, the DRAOR overall sample outperformed all other classes as they demonstrated limited predictive utility across outcomes.

While the findings were inconsistent with the hypothesis, caution is warranted when considering the utility of the classes in assessing recidivism risk. Fundamentally, these results suggest that the DRAOR predicts recidivism better when there is a wider variety of scores within the data, compared to when individuals with like scores are isolated into classes. As previously mentioned, latent groups are constructed to maximize the difference between groups while maximizing the similarity of individuals within groups (Miller et al. 2009; Vermunt & Magidson, 2002). Marsh et al. (2009) affirmed that due to the limited degree of variability within each latent class, valuable information is lost, resulting in a reduction of predictive accuracy. Specifically, each class would be comprised of both recidivists and non-recidivists, however, due to the nature of LCA, both would need to demonstrate similar item scores to be placed within the class. This would reduce the ability of the DRAOR to differentiate between the recidivists and non-recidivists within each class, restricting and distorting the predictive utility of the DRAOR with the recidivism outcomes. It is recommended that future research using latent variable models with risk assessments exclude the analysis of predictive accuracy. Moreover, variable-centered approaches may be more ideal when examining predictive validity due to the wider distribution of scores.

Theoretical Implications

The conceptual model of offender transition (Serin et al., 2010) was the main paradigm that informed the development of the DRAOR. This conceptual model incorporates a multitude of influences that inform the transition from an active criminal lifestyle to a prosocial lifestyle. This model incorporates internal and external risk and desistance correlates that are theorized to

influence pathways into and out of crime (Serin et al., 2010). Since the model hypothesizes that change is an iterative process that symbiotically examines external and internal factors of risk and need, it would be assumed that resultant LCA classes would reflect different proportions of these factors, representing different stages in the transition process. Additionally, it would be expected that recidivism outcomes would differ based on the distribution of these factors.

Bearing in mind that the classes were not developed specifically to replicate the model, and the DRAOR items do not explicitly capture all the items listed within the model as being related to risk and desistance correlates, the findings within the present study loosely support the transitional model. The resultant classes did reveal distinct differences between the distribution/pattern of scores on the DRAOR dynamic risk and protective items. Moreover, while there was limited utility in predicting the recidivism outcomes, the groups did demonstrate some differences in rates of recidivism.

Additionally, the assumption that a person-centered approach to risk assessment can complement and enhance risk assessment and case management strategies was supported. Five meaningful classes were identified with varying distributions of dynamic risk scores. While a class that was low across all items and a class that was moderate across all items were identified, the other three classes provided additional information about the individualized needs of sub-groups of justice-involved males. This exemplifies the goal of typology research. Person-centered techniques can help identify specific targets for treatment, by identifying meaningful clusters of individuals. If the results of the present study can be consistently and reliably replicated, this may provide a framework for case-specific treatment programs. In contrast, however, the predictive utility was severely diminished for the recidivism outcomes when the isolated classes were examined. The DRAOR total scores were more consistently predictive

across all recidivism outcomes (except for any new non-violent offence), this was likely due to the decreased variability of the scores within each class (Marsh et al., 2009). Therefore, it is recommended that both person-centered and variable-centered approaches continue to be used in subsequent research.

Implications for the Iowa Department of Corrections

The Iowa Department of Corrections assesses justice-involved individuals released to the community on the IRA and the DRAOR. In practice, the evaluator scores an individual on the DRAOR and modifies the case management plan based on item scores (Iowa Department of Corrections, 2019). Justice-involved individuals are linked to a variety of services based on their identified needs, including but not limited to; Case management counselling, education/vocation programs, parenting programs, domestic abuse programming, and substance abuse treatment programs (Iowa Department of Corrections 2019; Iowa Department of Corrections, 2009). The present study supports this direct targeting of needs identified by the DRAOR, due to the five resultant classes revealing distinct distributions of dynamic risk and protective factors.

The IDOC focuses on moderate and high-risk offenders to obtain additional services while in the community (Iowa Department of Corrections, 2019). In accordance with policy, a DRAOR assessment is not completed with clients who are identified as low risk (Iowa Department of Corrections, 2019). Specifically, the DRAOR is only administered to those assigned to a supervision level of three or higher (levels range from one to five). This is consistent with research that shows that low risk offenders require minimum programming while higher risk offenders require more intensive programming (Bourgon & Armstrong, 2005; Andrews & Bonta, 2006; Lloyd et al. 2014). The resultant classes in the present study demonstrated differences in their level of risk, which would aid community supervision officers

in determining the correct program dosage (e.g., the *low dynamic risk/high protective* class would require minimal programming while the *complex dynamic risk/complex protective* class would require more intensive programming). Additionally, two resultant classes, the *complex dynamic risk/complex protective* class and the *problematic employment/insufficient social support* class had high needs in the area of employment, consequently, more resources should be dedicated to increasing the employability of these justice-involved individuals through educational and vocational training.

Finally, four of the five resultant classes (excluding the *low dynamic risk/ high protective* class) demonstrated a lack of protective factors, with higher probabilities of scoring a zero (not an asset) or one (slight asset) across all protective factors. This signifies that a large portion of justice-involved males may benefit from services that directly target the development of protective factors (i.e., prosocial collateral contacts). Currently, Iowa's rate of recidivism is very high (38.8%; Iowa Department of Corrections, 2019), therefore ensuring services are developed to target areas of need to aid in the desistance process is vital. Chadwick et al., (2020) found when looking at the DRAOR subscales, a one-point increase in the protective scores corresponded to a 10% decrease in the likelihood of incurring a technical violation and an 18% decrease in the likelihood of incurring a new criminal charge: highlighting the importance of developing strength factors for justice-involved individuals. Therefore, it is also recommended that interventions that aid in the development of these factors are explored. These could include motivational interviewing, cognitive programs, behavioural programs, peer support, and social skills training.

Limitations

Though the analysis yielded distinct and meaningful classes, the present study was not without its limitations. Given that this was the first study to conduct an LCA with the DRAOR, the original pilot data was used to ensure fidelity (i.e., due to the extensive training community supervision officers received prior to delivering the assessment). However, the use of archival data did not allow for the examination of interrater reliability, and while the community supervision officers who conducted the DRAOR assessment were trained extensively, it is unknown if there was variability in the scoring among raters. Differences in experience level, attitudes and beliefs about the validity of risk assessments, feelings of burn-out/emotional exhaustion, and their level of commitment to their job may have affected how they scored the assessment (Latessa & Lovins, 2010; Schaefer & Williamson, 2018). Moreover, a convenience sample of community supervision officers who volunteered to participate in the DRAOR training and its subsequent assessment was used. These volunteers then selected the clients that were assessed on the DRAOR, potentially introducing biases into the study, and contributing to the discrepancies regarding the length of time on release.

Furthermore, while the present study utilized the initial DRAOR assessment for each participant, this variation in the length of time the justice-involved individual had been on community release before the initial assessment introduces some potential concerns. The average length of time on supervision, prior to the initial DRAOR assessment, was approximately one year. The stage immediately following release has been identified as the most problematic for individuals who were incarcerated, with rates of recidivism and conditional breaches peaking within the first few months of conditional release (Burnett, 2009). Notably, 56.7% of the sample had been on community release for at least six months before being assessed on the DRAOR. It

is possible that a group of individuals who would have received a DRAOR assessment at the beginning of their release and subsequently reoffended in less than six months were not adequately captured. As shown within the present study, recidivism rates for new charges were relatively low for the overall sample, specifically when referring to the instances of violent offences. This may have resulted in an artificially reduced recidivism rate, as many offenders had surpassed the most challenging period. Hence, the assessment was likely not completely reflective of their baseline risk. Further, the current data was restricted to the state of Iowa, meaning if one of the justice-involved persons within this sample re-offended outside of Iowa jurisdiction, this event would not have been captured within the present study. Additionally, as discussed previously, there is the potential of "risk decay" following time spent in the community offence-free, this may have distorted the impact of the IRA static risk scores on the resultant classes (Serin, 2020).

Furthermore, while the present study addressed the relationship between race and class membership, the interpretation of these results was limited. There was a large discrepancy between the proportion of White (71%; n = 362) and POC (29%; n = 148) individuals within the sample. As mentioned previously, POC are overrepresented within the Iowa Department of Corrections when compared to the general population (37% vs. 15% respectively; Iowa Department of Corrections, n.d.). This disparity could be indicative of differing pathways into and out of crime for POC, potentially suggesting that the overrepresented groups have varying and unique distributions of criminogenic needs. The unequal distribution of the current study may have diminished the potential differences between racial groups, with the large proportion of White individuals overshadowing any unique distributions of needs displayed by POC.

Lastly, this sample only included justice-involved males, resulting in a restricted sample that lacked consideration for the potential differences in the distribution of dynamic risk and protective factors for justice-involved females. Although the DRAOR is conceptualized as a gender-neutral approach (in line with the GPSL theory), these approaches are criticized for not considering that gender-neutral factors may manifest differently among women (Wagstaff, 2020). Additionally, feminist scholars suggest that women have unique experiences that contribute to their criminality that are different from men, such as victimization, mental health issues, self-efficacy, and trauma (Daly, 1992; Salisbury & Van Voorhis, 2009; Miller & Najavits, 2012; Short et al., 2013). Including a sample of justice-involved females within a person-centered analysis could potentially reveal such differences. The findings of the present study cannot be generalized to justice-involved female populations.

Future Directions

To expand and increase the validity of the current findings, several suggestions for future research are considered. It is recommended that the present study is replicated within different jurisdictions, across various populations, and over varying time points.

The DRAOR is regarded as a gender-neutral assessment tool (Scanlan et al., 2019), however, very few studies have focused on the utility of the DRAOR with female populations. Of the limited research, the use of the DRAOR with both males and females was supported (Yeberg et al., 2015; Scanlan et al., 2019). Interestingly, Yesberg et al., (2015) found that the DRAOR subscales (stable, acute, protective) were more predictive of recidivism (i.e., time to first offence leading to reconviction, including breaches of parole), for women. Further, when the subscales were examined independently, it was found that the acute subscale uniquely contributed to the model, suggesting that the acute subscale was the main contributing factor to

the ability of the DRAOR to predict recidivism outcomes for women. Examining classes disaggregated by gender could reveal specific class formations that are specific to women.

To date only a few typology studies have examined how the distribution of risk and strength factors are related to gender and how the incorporation of gender-responsive factors, such as childhood adversity, impacts the resultant groups (e.g., Wanamaker, 2020; Wagstaff, 2020). Therefore, future research should consider incorporating gender-responsive items into the analysis to determine how they impact the formation of the resultant classes. Notably, the Iowa Department of Corrections has recently implemented trauma, mental health, and self-efficacy as supplemental items to the DRAOR for case planning purposes (Corno, 2020). The inclusion of these supplemental items was based on Trauma Informed Correctional Care (TICC) and gender responsivity research (Corno, 2020). Each supplemental item is scored on a three-point scale (0-2), that follows the same scoring guide as the DRAOR items (i.e., 0 = no problem, 1 = slight problem, 2 = definite problem). While this represents a limited examination of these items, it is recommended that future typological research in Iowa incorporate these additional items to determine how they relate to typology membership.

Additionally, it is recommended that future studies address potential racial differences in class membership by including a sample that is equal in terms of racial proportion. Alternatively, future studies could adopt the method used by previous researchers for comparing justice-involved males and females, which have examined women and men independently, comparing the resultant class solutions (e.g., Hilterman, 2019; Wanamaker, 2020; Brown et al., 2020). Through this approach, a latent class analysis could be performed separately for those who identify as White and those who identify as POC, to determine if similar or different classes emerge. Furthermore, the relationship between the classes, race, and recidivism outcomes should

be explored, to examine potential differences between racial groups and community outcomes in relation to risk and strength factors.

Further, as the current study only utilized the initial DRAOR assessment (i.e., one-time point), the dynamic nature of the DRAOR items was not captured, resulting in the items being treated at static indicators (Brown et al., 2009). Therefore, it is recommended that future studies examine the distribution and formation of classes at different time points through Latent Transition Analysis (Collins & Lanza, 2010) or if individuals can be grouped into classes based on similar risk trajectories through Latent Trajectory Analysis (Muthén, 2004). Understanding how individuals change over time could aid in modifying case management plans, such as increasing or decreasing the frequency of contact or making new recommendations regarding treatment.

Finally, to examine the longer-term utility of classifying individuals based on risk and need assessment, longitudinal studies should be conducted to examine program outcomes. Numerous studies have cited the potential benefits of person-centered approaches to allow justice-involved individuals to be matched to programs that target their specific level of risk and specific distribution of criminogenic needs (e.g., Schwalbe et al., 2008). While this makes intuitive sense based on past research suggesting that programming is more effective when the dosage (Bourgon & Armstrong, 2005) and content match the risk and need level (Andrews & Bonta, 2016), to date there has been no research examining whether programming matched to class/profile risk and need distribution derived from person-centered approaches have improved program outcomes. Therefore, longitudinal studies that examine program outcomes (i.e., successful completion rates, program compliance, client change) should be conducted.

Conclusion

The present study was the first to examine a person-centered approach to risk assessment using the DRAOR. The findings presented support for the continued use of both the traditional variable-centered approach and the person-centered approach, with each method providing complementary ways of assessing the same phenomena. While criminogenic needs are important considerations in risk management, how these factors are distributed is also an important consideration. The person-centered approach identified five distinct classes derived from the DRAOR and IRA static risk scores, which differed in their distribution of dynamic risk and protective items scores. While utilizing a variable-centered approach provided the most consistent results when predicting recidivism outcomes, the utility of person-centered class was apparent. Collectively, these approaches provide additional information to aid community supervision officers in refining case management planning and providing program recommendations for justice-involved males.

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Appendix A

Dynamic Risk Assessment for Offender Re-Entry (DRAOR)

DRAOR Indicators	Score (Omit if Unknown)		
Stable Risk Indicators			
Peer Associations	Not a Problem 0	Slight Problem 1	Definite Problem 2
Attitudes Towards Authority	Not a Problem 0	Slight Problem 1	Definite Problem 2
Impulse Control	Not a Problem 0	Slight Problem 1	Definite Problem 2
Problem Solving	Not a Problem 0	Slight Problem 1	Definite Problem 2
Sense of Entitlement	Not a Problem 0	Slight Problem 1	Definite Problem 2
Attachment with others	Not a Problem 0	Slight Problem 1	Definite Problem 2
			Total Stable Risk Score
Acute Risk Factors			
Substance Abuse	Not a Problem 0	Slight Problem 1	Definite Problem 2
Anger/Hostility	Not a Problem 0	Slight Problem 1	Definite Problem 2
Opportunity/Access to Victims	Not a Problem 0	Slight Problem 1	Definite Problem 2
Negative Mood	Not a Problem 0	Slight Problem 1	Definite Problem 2
Employment	Not a Problem 0	Slight Problem 1	Definite Problem 2
Interpersonal Relationships	Not a Problem 0	Slight Problem 1	Definite Problem 2
Living Situation	Not a Problem 0	Slight Problem 1	Definite Problem 2
			Total Acute Risk Score
Protective Factors			
Responsive to Advice	Not an Asset 0	Slight Asset 1	Definite Asset 2
Prosocial Identity	Not an Asset 0	Slight Asset 1	Definite Asset 2
Realistic high Expectations	Not an Asset 0	Slight Asset 1	Definite Asset 2
Costs/Benefits	Not an Asset 0	Slight Asset 1	Definite Asset 2
Social Support	Not an Asset 0	Slight Asset 1	Definite Asset 2

Social Control	Not an Asset 0	Slight Asset 1	Definite Asset 2
			Total Protective Score

Risk Level	**DRAOR Cut-Off Score**
Low	≤ 2
Moderate	3 to 9
Moderate/High	10 to 22
High	≥ 23

Appendix B

Description of DRAOR Items[4]

Stable Items

1. *Peer Associations*

   This item refers to the nature and frequency of associations with criminal individuals. Peers can be partners, family members, friends, or acquaintances with whom the client spends free time. Criminal peers may be those who have committed crime in the past or would likely accept the client if the client were to commit criminal behavior in the present. Peers are individuals with whom the client has spent a relevant amount of time (e.g., at least semi-regular free time activities) in the past three months.

2. *Attitudes Towards Authority*

   This item refers to having a hostile, oppositional, antagonistic, or defiant attitude toward those in authority. Attitude refers to beliefs that authority figures (a) do not deserve to have power over them, (b) do not have a legitimate role to play in keeping order or enforcing rules, (c) do not "play fair" specifically when it comes to the client, or (d) do not deserve respect or consideration from the client. Also, (e) a client may describe avoiding their responsibilities or lying to authority figures as a "game" that everyone plays, suggesting that authority figures do not enforce rules for any higher purpose than to manipulate others and "win" power.

3. *Impulse Control*

   This item refers to either a pattern of (a) the client "doing the first thing that comes into their head" without thinking about the consequences, or (b) the client feeling so overwhelmed by impulses that they tend to give in and behave in ways they say they want to avoid.

4. *Problem Solving*

   This item refers to the client's ability to find solutions to their life problems in a way that takes them away from risk situations and criminal behavior. Good problem solving involves (a) a desire to find non-criminal solutions to problems, (b) thinking through options to decide on the best solution, and (c) taking action to make the solution a reality, which involves following through to find new solutions if setbacks come up in the process. Poor problem solving involves (a) a preference for criminal solutions to problems, (b) remaining inactive rather than engaging in proactive solution-finding, or (c) attempting to fix life problems in a way that causes more serious problems (e.g., puts the individual at risk for new crime, or the solution involves criminal activity).

5. *Sense of Entitlement*

   This item refers to an attitude of self-regard and self-centeredness, at the expense of regard for other's rights. Attitude refers to the clients' personal belief that (a)

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[4] Obtained from Serin (2007, 2015, 2017)

they deserve to get what they want, no matter the expense to others, (b) others will manipulate, coerce, or deceive them, if they don't manipulate, coerce, or deceive others first, (c) it's only fair that those who fight for their own rights will win out over those who are not as strong, and (d) people who lose out had it coming anyway.

6. *Attachment with Others*

   This item refers to a characteristic, ongoing lack of concern for others, resulting in social disconnection or problematic interpersonal attachments. Poor attachment with others may express as (a) general inattention or indifference to the emotions or needs of others, (b) a callous disregard for the ways others may feel hurt or betrayed by the client's actions, (c) short-term, superficial relationships characterized by opportunistic exploitation, or (d) complete disinterest toward feeling close to or maintaining relationships with others.

Acute Subscale

1. *Substance Abuse*

   This item refers to use of unauthorized substances, including illegal drugs and substances banned by supervision order, and the misuse of other substances, including prescription drugs and alcohol. The goal of this item is to assess recent problematic use and misuse of substances, especially to identify recent uncontrolled changes in typical substance use.

2. *Anger/Hostility*

   This item refers to the presence of either (a) "hot" emotions, such as high irritability, exasperation, fury, or rage (for example), or (b) attitudes that support the degradation of others, harm to others, or dehumanization of others. Both (a) anger and (b) hostility result in the client presenting as antagonistic, either by (a) behaving antagonistically, showing signs of a bad temper (i.e., clenched fists, speaking loudly, angry facial expressions), or (b) verbal expressions that others (specific individuals, or groups of individuals) do not deserve fair, ethical, or kind treatment. Unlike sadness (anxiety, depression), anger is focused outward, such that the client reports feeling upset at others (but, both types of emotions can occur simultaneously).

3. *Opportunity/Access to Victims*

   This item refers to the immediate availability of opportunities for crime. This is especially important to consider if the client has history victimizing a preferred victim (either one individual, such as an ex-partner, or a specified group of individuals, such as a sex offender with preference for child victims).

4. *Negative Moods*

   This item refers to the presence of unpleasant emotions, especially agitation, distress, anxiety, stress, or sadness. Unlike the "hot emotions" (anger), the focus of these negative moods is turned inward, such that the client reports feeling unsettled and upset inside of themselves (but both types of emotions can occur simultaneously).

5. *Employment*
   This item primarily assesses whether or not the client is currently employed. Other considerations surrounding employment have additional relevance. Specifically, (a) employability (i.e., does the client have the necessary skills to join the workforce?), (b) engagement (i.e., is the client currently satisfied with existing employment?), and (c) effort (i.e., is the client motivated to gain or maintain employment?).
6. *Interpersonal Relationships*
   This item refers to current problems in close interpersonal relationships in the client's life (which can include antagonism, victimization, breakdown, disconnection, social pressure to engage in criminal activity, etc.). The primary consideration should focus upon romantic partnerships, but close other relationships (with family, housemates, business partners, etc.) deserve consideration in the absence of a romantic partnership, or when there is severe distress or the breakdown of a prosocial relationship that is important to the client.
7. *Living Situation*
   This item primarily assesses whether or not the client is currently living in stable, long-term housing. Stable housing can be considered on a continuum from lack of any suitable housing, or homelessness (a definite problem), temporary or possibly problematic housing situations, such as residence at a halfway house, or "couch surfing" (a possible problem), to safe, suitable, long-term housing (not a problem). However, residing at a halfway house may be rated as definite problem if the client should currently be putting in effort to find other suitable housing, but is not doing so. Alternately, living in a supported residence may be rated as not a problem if the current situation may serve as a stable long-term solution, or the client has already made plans to enter safe, stable housing after leaving the residence.

Protective Subscale

1. *Responsive to Advice*
   This item refers to the client expressing openness to receive and take guidance for making lifestyle changes that will lead toward a long-term, crime-free lifestyle. This is the "Do I care, do I listen, and do I act?" component of the beliefs that support a process of desisting from crime.
2. *Prosocial Identity*
   This item refers to the client's internal self-image. This is the "Who am I?" component of the beliefs that support a process of desisting from crime. The purpose of this item is to assess whether the client can imagine and articulate a "future self" that feels comfortable, fulfilled, and satisfied in a fully non-criminal lifestyle.
3. *Realistic High Expectations*
   This item refers to clients' attitude toward change. This is the "I know it won't be easy, but I know it's possible" component of the process of desisting from crime.
4. *Costs/Benefits Supportive of Staying Crime-Free*

This item refers to clients' attitude toward the personal value of crime, and how this attitude compares or contrasts with their attitude toward the value of extending effort to stay crime-free. This is the "What do I get out of it and is it better than what I have?" component of the beliefs that support a process of desisting from crime.

5. *Social Support*

This item refers to whether clients have any meaningful relationships with non-criminal individuals, especially individuals who assist the client by offering relational (and / or material) support to the client.

6. *Social Control*

This item refers to the effects that existing prosocial relationships are having on clients who have supportive, non-criminal individuals in their lives. This item extends beyond the simple existence of prosocial others in the client's life and refers to the influence these individuals have on the client.

Appendix C

Ethics Approval

Office of Research Ethics
4500 ARISE Building | 1125 Colonel By Drive
Ottawa, Ontario K1S 5B6
613-520-2600 Ext: 4085
ethics@carleton.ca

CERTIFICATION OF INSTITUTIONAL ETHICS CLEARANCE

The Carleton University Research Ethics Board-B (CUREB-B) has granted ethics clearance for the changes to protocol to research project described below and research may now proceed. CUREB-B is constituted and operates in compliance with the *Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans* (TCPS2).

Ethics Clearance ID: Project # 104995 13-171

Principal Investigator: Ralph Serin

Co-Investigator(s) (If applicable): **Ralph Serin (Primary Investigator)**
Kaitlyn Wardrop (Co-Investigator)
Nick Chadwick (Co-Investigator)
Caleb Lloyd (Other)
Marina Guadagnin (Student Researcher: Undergraduate)
Bronwen Perley-Robertson (Student Research: Ph.D. Student)
Karen Jones (Student Researcher)

Project Title: **Validation of the Dynamic Risk Assessment for Offender Re-entry (DRAOR)**

Funding Source:

Effective: **May 26, 2021** Expires: **March 31, 2022**.

This certification is subject to the following conditions:

1. Clearance is granted only for the research and purposes described in the application.
2. Any modification to the approved research must be submitted to CUREB-B via a Change to Protocol Form. All changes must be cleared prior to the continuance of the research.

3. An Annual Status Report for the renewal or closure of ethics clearance must be submitted and cleared by the renewal date listed above. Failure to submit the Annual Status Report will result in the closure of the file. If funding is associated, funds will be frozen.
4. During the course of the study, if you encounter an adverse event, material incidental finding, protocol deviation or other unanticipated problem, you must complete and submit a Report of Adverse Events and Unanticipated Problems Form.
5. It is the responsibility of the student to notify their supervisor of any adverse events, changes to their application, or requests to renew/close the protocol.
6. Failure to conduct the research in accordance with the principles of the *Tri-Council Policy Statement: Ethical Conduct for Research Involving Humans 2nd edition* and the *Carleton University Policies and Procedures for the Ethical Conduct of Research* may result in the suspension or termination of the research project.

Special requirements for COVID-19:

If this study involves in-person research interactions with human participants, whether on- or off-campus, the following rules apply:

1. Upon receiving clearance from CUREB, please seek the approval of the relevant Dean for your research. Provide a copy of your CUREB clearance to the Dean for their records. See Principles and Procedures for On-campus Research at Carleton University and note that this document applies both to on- and off-campus research that involves human participants. Please contact your Dean's Office for more information about obtaining their approval.
2. Provide a copy of the Dean's approval to the Office of Research Ethics prior to starting any in-person research activities.
3. If the Dean's approval requires any significant change(s) to any element of the study, you must notify the Office of Research Ethics of such change(s).

Upon reasonable request, it is the policy of CUREB, for cleared protocols, to release the name of the PI, the title of the project, and the date of clearance and any renewal(s).

Please email the Research Compliance Coordinators at ethics@carleton.ca if you have any questions.

CLEARED BY: **Date: May 26, 2021**

Bernadette Campbell, PhD, Chair, CUREB-B

Natasha Artemeva, PhD, Chair, CUREB-B