Validating the Dynamic Risk Assessment for Offender Re-entry (DRAOR) in a sample of U.S. probationers and parolees

by

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Abstract

The foundation for effective case management is rooted in the use of a validated risk assessment. The present study sought to validate the Dynamic Risk Assessment for Offender Re-entry (DRAOR) among a sample of probationers and parolees (n = 391) in the state of Iowa. Scores across the DRAOR domains were able to differentiate between recidivists and non-recidivists when examining technical violations and any recidivism, although were unable to differentiate between those offenders who were re-arrested and those who remained crime free. An examination of the psychometric properties of the scale suggested that the DRAOR is a valid risk assessment tool. Additionally, Stable dynamic risk factors represented the strongest predictor of technical violations, although were unable to predict rearrest. The predictive utility of the various domains (i.e. Stable, Acute, and Protective) suggested that case managers would benefit from utilizing the DRAOR in the everyday supervision of offenders.

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In recent decades there has been an increase in the overall population of incarcerated offenders (Public Safety Canada, 2012). As a function of this increase, more offenders are being released to the community under supervision orders. Research investigating the revocation rates of offenders released on community supervision suggests that the correctional system may not be effectively managing this subset of offenders (Brown, St. Amand, & Zamble, 2009; Burnett, 2009). The transition from incarceration to community supervision requires the offender to make drastic changes in preparation for a crime free lifestyle. However, it appears that the current case planning strategies utilized by community supervision officers may not be comprehensive enough, potentially leaving the offender ill prepared for reentry to the community (Bonta, Rugge, Scott, Bourgon, & Yessine, 2008). One area of research that has received considerable attention for more than 3 decades is offender risk assessment. Risk assessment is critical to the management of offenders both in prisons and community corrections; in particular it informs the initial case plan and program dosage to mitigate risk. Although the assessment of risk appears vital to managing offenders, there is considerable debate regarding which assessment strategies have the greatest utility. The purpose of this study is to examine the predictive utility of a recently developed dynamic risk assessment scale aimed at enhancing the case management process.

Andrews and Bonta (2010) argue that sound assessment instruments are rooted in theory that directly guides the selection of relevant variables for assessment. The Personal, Interpersonal, and Community-Reinforcement (PIC-R) perspective represents a social learning theory of criminal conduct that asserts that criminal behaviour is the result of learning

experiences in conjunction with personal and situational factors. A meta-analytic examination of various predictors of recidivism suggested that these personal and situational factors are the most relevant considerations when predicting future reoffending. Specifically, antisocial attitudes (k = 67, r = .18), antisocial associates (k = 27, r = .21), antisocial personality (k = 63, r = .21) and criminal history (k = 282, r = .16) consistently demonstrated the strongest relationship with offender outcome (Gendreau, Little, & Goggin, 1996). In addition to selecting the most relevant variables to assess, Andrews and Bonta (2010) argue that ensuring assessment strategies are theoretically supported will lead to enhanced utility including risk management and case preparation.

One integral aspect of PIC-R is the importance of assessing an individual across multiple domains (e.g. substance use, antisocial personality). Comprehensive assessment procedures will ensure an accurate representation of an offender's circumstances. Not only does offender assessment need to be comprehensive, it is also important to ensure that dynamic covariates of criminal behaviour are measured and targeted. These dynamic factors (e.g. procriminal attitudes and substance use) have been demonstrated to change (Brown et al., 2009; Vose, Lowenkamp, Smith, & Cullen, 2009), and thus represent important treatment targets for community supervision officers to emphasize throughout ongoing sessions with clients. It is anticipated that promoting positive change among these dynamic risk factors will reduce an offender's risk to reoffend (Douglas & Skeem, 2005; Hanson & Harris, 2000; Kraemer, Kazdin, Offord, Kessler, Jensen, and Kupfer, 1997). Measuring and encouraging change on dynamic risk factors is central to effective offender management; further, there is the added benefit of utilizing these dynamic risk factors to guide the intensity of intervention efforts. Knowledge of an offender's detailed risk level, across multiple domains, will inform officers regarding the intensity of treatment

required to reduce the overall level of risk. Lastly, a thorough assessment strategy can provide a recommended treatment delivery strategy tailored to each offender (e.g. considering an offender's cognitive ability when delivering treatment).

In addition to the importance of theoretical support for a risk assessment procedure, Andrews and Bonta (2010) argue that adherence to the Risk, Need, and Responsivity (RNR) principles will enhance correctional intervention techniques. These principles posit that higher dosages of intervention techniques must be directed to those offenders who demonstrate the highest risk. The need principle emphasizes that interventions should be directed at an offender's criminogenic needs (e.g. antisocial attitudes); those needs that are directly associated with criminal behaviour and that, when positively changed, lead to reductions in risk. Lastly, the responsivity principle maintains that any treatment that is provided must be done so in a manner that is receptive to the offender. It is imperative that treatment providers consider education level, learning style, culture, and gender differences when selecting and administering appropriate treatment. According to Andrews and Bonta (2010) when these principles are adhered to, correctional interventions are more effective, and this has been demonstrated both within correctional institutions (Dowden & Andrews, 2004) and among community corrections (Bonta et al., 2011; Bourgon and Gutierrez, 2012). By examining these principles it is evident that an accurate risk assessment is integral to the initial stages of case management. If a risk assessment does not highlight an offender's criminogenic needs, intervention efforts may be directed at irrelevant factors. Similarly, utilizing an inaccurate assessment may incorrectly categorize some offenders as lower risk when in fact they demonstrate higher risk. Although the principles of PIC-R and RNR emphasize the need for accurate and comprehensive risk assessments, in practice, assessment strategies have differed markedly in the past.

Generations of risk assessments

The initial risk assessment approach taken by correctional decision makers was a subjective method known as unstructured clinical judgement. According to Bonta's classification of risk assessment, these strategies represent the first generation of risk assessments. This process involved the reliance on a professional's opinion, judgement, and intuition to render a decision regarding an offender's risk (Bonta, 1996). There are no specific guidelines to follow when considering a case, which resulted in a lack of consistency and agreement between clinicians. Despite the disadvantages, this assessment technique remains the preferred method by many correctional decision makers (Boothby & Clements, 2000).

In an effort to increase consistency between decision makers, the second generation of risk assessments evidenced a transition towards a more objective approach with the use of actuarial tools (Bonta, 1996). These instruments include a set of factors that have been found to correlate with recidivism, allocating more weight to factors that demonstrate a stronger relationship with crime. Actuarial tools consist primarily of static risk factors which are typically factors that are historical and not able to change (e.g. criminal history, age at first arrest). Utilizing a meta-analysis, Campbell, French, and Gendreau (2009) examined the predictive accuracy of risk assessment strategies. Results indicated that actuarial tools provided more accurate point estimates of general and violent recidivism, as compared to clinical judgment strategies. Actuarial tools have the limitation that they are unable to measure fluctuations in risk and provide little guidance for intervention and risk management efforts (Wong & Gordon, 2006). Static factors do not demonstrate whether intervention efforts were successful or when an offender is particularly vulnerable to commit another offense (as evidenced by an increase in

overall risk). However, static assessments are important for establishing an initial level of risk, and corresponding supervision intensity that subsequently informs initial correctional planning.

The third generation of risk assessments built on the second generation in that these assessments continued to measure the static risk factors that correlated with recidivism but also included theoretically relevant dynamic risk variables. Dynamic variables are those risk factors that demonstrate the ability to change (e.g. employment, criminal associates, substance use, etc.) either rapidly, often referred to as acute, or gradually, referred to as stable (Bonta, 1996; Hanson & Harris, 2000). The underlying assumption with these assessments is that risk is not entirely stable and can change as a result of a variety of factors, including treatment quality, environmental factors, and protective factors (Andrews & Bonta, 2010). Often referred to as risk-needs instruments, these assessments allow decision makers to identify the offender's pertinent criminogenic needs that require intervention to reduce their risk to reoffend. Campbell et al. (2009) conducted a meta-analysis to examine the predictive ability of the various generations of risk assessments. Their results indicated that third generation instruments slightly outperformed second generation assessments for the prediction of violent recidivism. Although third generation assessments demonstrated a higher average effect size, the difference was marginal, and the authors concluded that each instrument (both second and third generations) could predict violent recidivism with at least moderate levels of success (Campbell et al., 2009).

Recently there has been the development of a fourth generation of risk assessments (Andrews, Bonta, & Wormith, 2006). These assessments consist of a case planning system that assists correctional staff with allocating resources to address the offender's most problematic criminogenic needs. With an emphasis on case planning, fourth generation assessments have the unique ability to highlight specific responsivity factors relevant to an offender and inform the

treatment service that would be of most benefit. Further, by emphasizing the amenability of dynamic risk factors, multiple assessments of risk are encouraged, enhancing direct clinical supervision by correctional staff members (Andrews et al., 2006).

Although the generations of risk assessments include a detailed discussion of the previous and current practices utilized by correctional decision makers, this categorization is not exhaustive. Structured Professional Judgement (SPJ) is an assessment approach that is not included in Bonta's classification. This approach involves the evaluation of empirically based risk factors by a clinician (Borum, 1996). For practical use, these scales do not rely on a total score to represent the probability of future reoffending, but rather provide recommendations to prevent recidivism and recognize what potential scenarios (type of offending, type of victim, etc.) are likely to unfold. These tools do not fit within the second or third generation taxonomy, but they do provide more structure and assess a broad range of empirically validated risk factors than compared to first generation assessments. Results have not definitively supported the SPJ approach over actuarial approaches (Skeem & Monahan, 2011), although research has suggested that SPJ can predict client outcome with moderate accuracy (Wilson, Desmarais, Nicholls, Hart, & Brink, 2013). The focus of the current study is to examine the predictive accuracy of a recently developed SPJ measure, the Dynamic Risk Assessment for Offender Re-entry (DRAOR; Serin, 2007; Serin, Mailloux, & Wilson, 2010), among a sample of general offenders under community supervision.

In contrast to Bonta's (1996) generations of risk assessments, Hanson and Morton-Bourgon (2009) have proposed an alternative method of classifying risk assessment strategies. In an initial review of risk assessment procedures, Hanson (1998) suggested that there are three plausible approaches to risk assessment, particularly with sexual offenders. Hanson suggested

that a *guided clinical approach* involves expert evaluators considering a wide range of empirically validated risk factors, alongside their clinical opinions, to render an overall appraisal regarding the offender's recidivism risk. *Pure actuarial* approach determines an offender's level of risk using a limited set of predictors that are combined using a predetermined weighting system. Lastly, an *Adjusted actuarial* method begins with an actuarial prediction, but can be overridden by an expert's opinion after considering other relevant factors not included in the actuarial measure.

Recently, Hanson and Morton-Bourgon (2009) further elaborated on this classification to include *Mechanical* approaches. Mechanical scales are largely based on theory and have rules for combining the items to reach a final score; however these overall scores are not linked to a probability estimate (i.e. expected recidivism rate). A final category consists of an u*nstructured* approach to risk assessment which, similar to Andrews and Bonta's 1st generation, does not provide recommendations for which factors to consider, nor is a method for combining the risk factors specified in advance. Results comparing the average predictive utility of each of these assessment strategies revealed that actuarial and mechanical scales outperformed structured professional judgement when predicting sexual recidivism. When utilized to predict violent recidivism, results suggested that actuarial methods outperformed mechanical strategies.

Although the field of risk assessments have progressed substantially over the years, there remain some limitations to current practices. A trend towards improving risk assessments has transpired which has directed attention towards those dynamic risk factors that are emphasized in third and fourth generation risk assessments. Although the importance of these risk factors has been highlighted (e.g. Andrews & Bonta, 2010; Hanson & Harris, 2000; Kraemer et al., 1997), the conclusions that can be made from these factors are still unclear. As indicated, dynamic risk

factors have the potential to signal the imminence of a new crime and may even predict the type of future criminal behaviour. As risk assessments continue to develop, identifying the relevance of the fluctuations among dynamic risk factors will provide a greater understanding regarding the appropriate methods and timing of intervention.

Conceptualizing dynamic risk

Previously, once an offender's level of risk was determined, pending no further increase due to new criminal charges, there was no opportunity to document changes. As discussed, initial risk assessment procedures emphasized static risk factors and failed to recognize that an individual's level of risk could vary over time. As focus has shifted from purely static models to incorporate dynamic factors, research has begun to surface which highlights the importance of considering fluctuations in risk and how these changes may impact release planning, treatment planning, and recidivism (Brown et al., 2009; Caudy, Durso, & Taxman, 2013; Hanson & Harris, 2000; Howard & Dixon, 2013; Jones, Brown, & Zamble, 2009; Lewis, Olver, & Wong, 2012).

Among the literature there remains ambiguity surrounding what exactly constitutes a truly dynamic risk factor. Additionally, the literature remains uncertain regarding how these factors contribute to an offender's overall risk and their particular utility when predicting future involvement in crime. Skeem and colleagues (Douglas and Skeem, 2005; Skeem and Mulvey, 2002) argue that to accurately represent an offender's level of risk you must differentiate between risk status and risk state. Risk status emphasizes static risk factors that are not expected to change over time, and therefore are of little utility when identifying intervention services or managing the offender. Risk state however involves an analysis of various factors that could influence change in an offender's level of risk. Risk state can be impacted by changes in biological, psychological, and social variables that are occurring in one's life. Further, these

variables could change rapidly (e.g. level of anger) or tend to be gradual (e.g. antisocial attitudes). Both fully static as well as dynamic factors contribute to an individual's risk state which allows for a comprehensive evaluation of an offender's risk, ultimately contributing to more effective offender management (Douglas & Skeem, 2005).

Hanson and Harris (2000) also distinguish between stable and acute dynamic risk factors. They define stable dynamic risk factors as those factors that are not expected to change frequently, suggesting a time frame of months or years. Acute dynamic risk factors are anticipated to change rapidly, over days, sometimes even hours. Accordingly, intervention efforts should be directed at the stable dynamic risk factors as these are the factors that, when changed, are anticipated to lead to improvements in the offender's overall level of risk. To support this recommendation, Hanson and Harris (2000) emphasized that among a sample of 409 sex offenders the prevalence of the stable dynamic risk factors were responsible for the differentiation between recidivists and non-recidivists. As a result, it appears that acute dynamic factors may represent the absence of effective coping and problem solving skills that would otherwise allow offenders to successful handle problematic situations that increase propensity for future crime.

Kraemer and colleagues (1997) further argue that dynamic risk factors could be considered causal if they meet certain criteria. In order to sufficiently conclude that a dynamic risk factor is causal it must be demonstrated that it can be changed through intervention or inadvertently (e.g. aging). The presence of the risk factor must also increase the offender's probability of recidivism. Lastly, it must be demonstrated that the change in risk preceded the outcome.

The inclusion of dynamic risk factors within risk assessments provides treatment providers and case managers the opportunity to evaluate the rehabilitative efforts that have been employed. By examining the changes in risk one can determine if the intervention has yielded desirable effects or if the strategies need to be altered to increase efficacy. Further, considering variables relevant to an offender's level of risk, correctional workers are better prepared to make informed decisions regarding release or additional treatment services.

In an effort to gain an understanding of the influence of dynamic risk factors on future reoffence, Zamble & Quinsey (1997) conducted a comprehensive retrospective analysis of 311 offenders who reoffended after being released from prison. A small sample of offenders (n = 36) who did not reoffend after release from prison served as a control group. Offenders were interviewed to understand their circumstances prior to committing a new offence (or not reoffending as was the case for the nonrecidivists). Participants were specifically asked about their living arrangements, employment, their leisure time, and relationships. Offenders were also asked to answer a series of questionnaires that assessed depression, anger, anxiety, and substance use. Generally, results indicated that compared to those offenders who remained in the community, reoffenders lived unsettled lives with frequent moves, frequent unemployment, and unstable relationships. When offenders were asked to recall potential problems that immediately preceded their most recent offence the most commonly noted problems included interpersonal conflicts, substance abuse, and financial problems. Further, reoffenders noted that feelings of frustration, depression, anxiety, and anger were all common during the month preceding the reoffence. Overall it appeared that those who reoffended demonstrated poor coping skills compared to those offenders who successfully remained in the community. This study provided the foundation for our understanding of dynamic risk factors and highlights how critical these

risk factors may be when predicting the imminence, and the overall probability, of a future offence.

More recent studies have supported these initial findings with results suggesting that offenders who reoffend often demonstrate higher scores on dynamic risk factors as compared to offenders who successfully remain crime free (e.g. Brown et al., 2009; Howard & Dixon, 2013; Miller, 2006; Schlager, & Pacheco, 2011; Simourd, 2004). Among other considerations, Hanson and Harris (2000) compared dynamic risk factors among a sample of sex offenders who reoffended and a sample of sex offenders who had not reoffended. Results indicated that recidivists were more likely to drop out of treatment and display deterioration in their behaviour, whereas the non-recidivists' behaviour generally improved throughout the course of the supervision. Similar results were reported by Hudson, Wales, Bakker, and Ward (2002) whereby sexual reoffenders had more deviant post-treatment scores, and demonstrated less prosocial improvement than non-reoffenders. Similarly, among a sample of general offenders, significant change was noted amid various dynamic risk factors including: employment, leisure time, stress, negative affect, coping, and criminal attitudes (Brown et al., 2009; Jones et al., 2010). Although still in its infancy, there is a growing body of literature supporting the increased attention that dynamic risk factors have received. By demonstrating that these factors do indeed change, treatment providers have concrete targets, and evaluators are able to develop criteria that can be used to measure the efficacy of the treatment. Although these initial results emphasizing dynamic factors are promising, there remain methodological issues, particularly with measurement, that have impacted the utility of such factors when predicting offender outcome.

Additionally, there remains ambiguity surrounding the relative importance of dynamic factors when predicting recidivism alongside static factors. A comprehensive examination

among two unique samples of offenders serving community supervision orders in a Midwestern state examined the predictive and incremental validity of a group of dynamic risk constructs (Caudy et al., 2013). Results from a multivariate regression model suggested that among one sample (n = 22,563) antisocial attitudes, antisocial peers, and education/employment domains were predictive of recidivism after controlling for static risk factors (i.e. criminal history, sex, age). A slightly different pattern emerged among the second sample (n = 2,409) whereby antisocial peers and alcohol/drug problems emerged as significant predictors of reconviction after controlling for the same static risk factors (Caudy et al., 2013). The findings question the overall utility of dynamic factors in the prediction of recidivism above static risk considerations, although highlight their importance in identifying intervention targets given the relationship with recidivism.

Examining the changeability of risk

Although previous studies typically indicated that dynamic risk variables were relevant when predicting recidivism, most studies have failed to truly measure the nature of a dynamic risk variable. By examining the risk factor at a specified period of time, researchers are treating a dynamic variable as static. Kraemer et al. (1997) have recommended that at least two assessments of risk are necessary to accurately capture change, whereas other researchers have suggested that at least 3 distinct assessments of dynamic risk should be conducted at specified time intervals (Brown et al., 2009). Using a sample of 136 male federal offenders Brown and colleagues (2009) conducted three assessments of dynamic risk to evaluate change in risk factors and the overall contribution of dynamic factors to the prediction of recidivism alongside static risk. Results from a cox regression survival analyses that incorporated a series of time dependent covariates (e.g. negative affect, employment, criminal association, coping ability, etc.) revealed

significant within-individual change among a subset of offenders (*n* = 86) who did not reoffend during the follow up period. These offenders demonstrated reductions in problems areas including: employment problems, leisure problems, perceived global stress, negative affect, substance abuse problems and social support. The strongest model for predicting revocations included both static and dynamic risk factors. When static and dynamic risk, as measured prior to release, were combined the prediction model significantly outperformed the solely static model. Similarly, the combined static and dynamic risk, as measured in the community over time, also significantly improved the prediction above the static only model (Brown et al., 2009).

Others have employed alternative techniques whereby change among dynamic risk variables is used to predict offender outcome (Lewis et al., 2012; Miller, 2006, Vose, Lowenkamp, Smith, and Cullen, 2009; Vose, Smith, and Cullen, 2013). Among a large sample (*n* = 2,849) of adult offenders under community supervision Vose et al. (2009) found that the difference between two assessments of the LSI-R significantly predicted recidivism for both males and females. In a recent investigation, Vose et al. (2013) updated their initial study to examine the predictive utility of change scores across different levels of risk. Results suggested that change among risk levels (i.e. moving from moderate risk to low/moderate) was more salient for offenders initially classified as higher risk. When change (i.e. reduction in risk) was observed among those offenders classified as high risk there was a corresponding 16% reduction in the recidivism rate (Vose et al., 2013). After controlling for race, age, gender, risk, and supervision category, multivariate logistic regression analyses revealed that change on the LSI-R was a significant predictor of recidivism. However, effect sizes at both assessment times were low (R_N^2 = .04 for Model 1 and .09 for Model 2), indicating that a more dynamic measure of risk may be required to obtain a larger effect.

A recent investigation examined the predictive validity of various conceptualizations of change among risk factors. A sample of 828 adult probationers who were assessed with the LSI-R and subsequently reassessed within three years, were followed for a year to determine if new arrests had been recorded. Labrecque, Smith, Lovins, and Latessa (2014) evaluated a series of multivariate logistic regression models to ascertain whether percentage change between initial assessment and reassessment enhanced the prediction of rearrest compared to examining raw change. Results indicated that raw change and percentage change significantly predicted rearrest, although the percentage change model yielded a higher overall effect (R_N^2 = .11 vs. R_N^2 = .10). Specifically, the results suggested that for every 1% decrease in total score, there was a 6.25% reduction in overall risk to be rearrested. Overall, this study highlighted the utility of incorporating information regarding offender change in case management decisions (e.g. making recommendations for intervention if an offender demonstrates an increased risk in a particular domain).

Among a large sample of offenders in the United Kingdom, Howard and Dixon (2013) examined the dynamic validity of a variety of risk indicators. The authors reported that the dynamic risk factors did demonstrate change throughout the follow up, particularly among alcohol misuse and temper control factors. Similar to previously reported studies, the results suggested that reductions in dynamic risk were evident for all offenders, but more pronounced for those offenders who did not reoffend. When change among dynamic factors was considered in a prediction model, results suggested that there was a contribution above and beyond models that only considered static risk factors and the initial dynamic risk assessment. Suggesting that when those measured changes were included in the prediction of violent reoffending the accuracy of the prediction was heightened (Howard & Dixon, 2013). Similar results were

obtained in a retrospective analysis of dynamic risk factors among high risk offenders (Lewis et al., 2012). Offenders' level of violence risk was assessed at two time points (before and after treatment) and a total change score was calculated to determine if change among dynamic factors was predictive of violent recidivism. Results indicated that change scores were significantly related to violent recidivism; suggesting that those offenders who demonstrated more change evidenced lower rates of violent recidivism. Further, the dynamic items that were assessed increased the prediction of violent recidivism above a prediction model including only static factors (Lewis et al., 2012).

Although some studies have found that the inclusion of dynamic risk increased the overall prediction of recidivism, the results are not conclusive. An examination of static and dynamic risk factors among 133 male offenders released into the community in Texas suggested that change among dynamic factors was not related to offender outcome (Morgan, Kroner, Mills, Serna, & McDonald, 2013). Offenders were assessed a total of 7 times over 6 months in an effort to capture the fluctuations that may be apparent among dynamic factors. Results suggested that dynamic risk factors did not significantly improve predictive accuracy above static risk. The authors do emphasize that the 6 month follow up period was too brief to capture the potential offending patterns of the offenders, but nonetheless highlight that this is still a growing body of literature and some uncertainties remain. Similar results regarding change among dynamic factors were also obtained by Hanson, Harris, Scott, and Helmus (2007). In an attempt to advance risk assessment procedures for sex offenders, the authors analyzed various stable and acute dynamic risk factors alongside a measure of static risk. Change among a measure of stable dynamic risk was not predictive of any type of recidivism (i.e. sexual, violent, and any recidivism) and change among the acute risk factors yielded similar findings. Results did indicate

that averaging the acute ratings over longer periods of time increased the predictive accuracy. Further, the inclusion of the stable and the acute dynamic risk factors did significantly improve the prediction of recidivism.

Incorporating protective factors

Although the inclusion of dynamic risk factors remains to be an important consideration, recent research has argued that current risk assessment practices are biased in that they fail to consider positive influences or behaviours that the offender demonstrates (Rogers, 2000). Similar to definitions of dynamic risk, there remains dissent when conceptualizing what these positive behaviours and influences are and how they interact with an offender's risk factors. Generally, these behaviours and influences are known as protective factors. Some argue that protective factors represent one side of a continuum with the opposite side being a risk factor (Hawkins, Catalano & Miller, 1992; Webster, Martin, Brink, Nicholls, & Middleton, 2004). Proponents of this conceptualization would argue that any given factor could be scored as either a vulnerability (thus a risk factor) or a strength. Protective factors may also represent the absence of risk factors; suggesting that if an offender does not display problems in the area of antisocial attitudes, it would be viewed as a protective factor. Finally, protective factors have been conceptualized as independent from risk, indicating that offenders may demonstrate multiple protective factors and multiple risk factors simultaneously (Costa, Jessor, & Turbin, 1999; Jessor, Van Den Bos, Vanderryn, Costa, & Turbin, 1995). Displaying a high expectation of success is an example of this conceptualization of protective factors as the inverse does not represent an increased risk, nor does it prevent an individual from also displaying a risk factor such as substance abuse. This is the definition that was used in the development of the DRAOR as the protective factors that are included exist without a corresponding risk factor.

Research investigating the relationship between protective factors and recidivism among general offenders is scarce. Drawing upon research with juvenile offenders there are two frameworks that detail how protective factors relate with recidivism (Rutter, 2000). According to a compensatory model risk and protective factors are cumulative, with each risk factor increasing the odds of recidivism and each protective factor decreasing the odds of recidivism. Under this model, it is the number of factors present that is more important than the specific factor itself. The second proposed model is the interactive model which asserts that protective factors are only relevant when there are risk factors present. Under this model, the impact of protective factors varies depending on the level of risk, potentially lessening the impact of risk when protection is high rather than when protection is low or absent.

To examine the relationship between protective factors and negative outcomes Fitzpatrick (1997) had youth report on their fighting tendencies and their social bonding with parents and teachers. Albeit a narrow selection of protective factors, one of the study objectives was to ascertain whether protective factors mediated the relationship between risk and negative outcome or buffered an individual against a negative outcome. Results supported a buffering model suggesting that risk factors appear more salient when protective factors are non-existent or minimal. These findings reinforce the definition proposed by Rutter (1985; 1987) which emphasized the ability of protective factors to modify or improve a person's response to some hazard known to increase the probability of a negative outcome.

In an effort to evaluate potential relationships between protective factors and recidivism Ullrich and Coid (2011) examined 15 proposed protective factors among a large sample of offenders who were followed for an average of 5 years. Of the 15 factors examined, results indicated that items including social support, emotional support, spare time spent with prosocial

family and friends, involvement in religious activities, and closeness with others demonstrated protective effects for violence after release from incarceration. After controlling for risk, spare time spent with family or friends demonstrated a significant independent effect on recidivism such that those who indicated that those that endorsed this item experienced lower rates of recidivism during the follow up periods, regardless of the level of risk.

In addition to comprehensively examining an offender's risk and rehabilitation potential, emphasizing protective factors is expected to foster a therapeutic alliance, promote recovery, and possibly motivate the offender as they are aware that their progress is recognized by their supervising officer (Ullrich & Coid, 2011). Further, research on desistance from crime (i.e. crime cessation) suggests that protective factors may represent some of the internal and external mechanisms that underlie the process of exiting crime (Serin & Lloyd, 2009). Through a qualitative examination of high risk offenders, HaggÅrd, Gumpert, and Grann (2001) reported that offenders who successfully remained crime free for a period of 5 years indicated that positive support from family and recognizing the costs associated with crime were critical to their success in the community.

With the emergence of literature identifying the importance of measuring protective factors along with static and dynamic risk, various assessments have recently been developed and implemented. Generally, these instruments have been developed for use with specific offender samples (i.e. forensic inpatients, juvenile offenders) and have often not been applied to general offenders. A description of the various instruments that incorporate protective factors follows, along with initial results as these scales move through the validation stage.

The Short-Term Assessment of Risk and Treatability (START; Webster et al., 2004) is a SPJ approach that provides a framework for structuring the assessment of dynamic risk and

protective factors. This measure incorporates 20 items that can be scored as either a vulnerability or an asset. The scale aims to identify an individual's short term risk associated with mental, substance use, and personality disorders. In a study aimed at investigating the predictive ability of START Desmarais, Nicholls, Wilson, and Brink (2012) found that total scores significantly predicted verbal aggression, physical aggression against others, and physical aggression against objects. Results also indicated that mean vulnerability scores were higher among those patients that demonstrated any form of aggression over the follow up period. Similarly, mean strength scores were higher for patients who did not display any aggressive tendencies throughout the follow up (Desmarais et al., 2012). An adolescent version of START has also been developed and administered to adolescent offenders (Viljoen et al., 2012). A sample of 90 adolescent offenders were assessed and followed for a three month period. Results suggested that vulnerability total scores were associated with substance use, aggressive offences, and total offences. Strength total scores were inversely correlated with adverse outcomes, although strength scores appeared to be less robust predictors of all adverse outcomes as compared to vulnerability scores and final risk estimates.

The Structured Assessment of Protective Factors for violence risk (SAPROF; de Vogel, de Ruiter, Bouman, & de Vries Robbé, 2009) was developed as a dynamic addition to the Historical Clinical Risk management-20 (HCR-20; Webster, Douglas, Eaves, & Hart, 1997). The instrument consists of 17 items, 2 static factors, and 15 protective factors that are assessed to identify potential goals or targets for intervention. The SAPROF is designed to prospectively prevent recidivism by informing treatment rather than be used as a prediction tool. In a retrospective validation de Vries Robbé, de Vogel, and de Spa (2011) found that SAPROF total scores were able to significantly predict non-recidivism of a violent offence over three follow up

periods (r_{pb} = -.35 at 1 year, r_{pb} = -.38 at 2 years, and r_{pb} = -.35 at 3 years). Results also demonstrated that the dynamic nature of the factors was accurate as individual change was apparent when comparing pre and post treatment assessments. Overall psychometric properties of the SAPROF appear sufficient (de Vries Robbé et al., 2011). Further, results have suggested that, when combined with a dynamic measure of risk, the inclusion of protective factors among the SAPROF has improved the overall prediction of recidivism at both a three year follow up and a long term follow up (de Vries Robbé, de Vogel, & Douglas, 2013). Overall results suggest that the SAPROF is a useful addition to structured assessments but has only been utilized among forensic samples.

The Structured Assessment of Violence in Youth (SAVRY; Borum, Bartel, Forth, 2006) is an instrument that includes ten historical risk factors, eight social/contextual risk factors, eight individual risk factors, and six protective factors that have been empirically related to reductions in violent behaviour among youth (Rennie & Dolan, 2011). Recent studies have analyzed the impact of the SAVRY protective factors and results have demonstrated that protective factors appear to mitigate the risk of violent reoffending for high risk adolescents (Lodewijks, de Ruiter, & Doreleijers, 2010). Rennie and Dolan (2010) found that participants who had not reoffended after being released for 12 months had significantly more protective factors compared to those adolescents who reoffended during the follow up period. Similar results were obtained by Richard (2011) whereby youth who had desisted from violent offending had significantly more protective factors and fewer symptoms of conduct disorder. Further, the SAVRY Protective score was predictive of desistance from violent offending during a 10 year follow up (AUC = .62, p < .01; Richard, 2011).

The instruments discussed thus far have been developed for specific samples of offenders. Recently the Inventory of Offender Risk, Need, and Strength (IORNS; Miller, 2006) has been developed which is intended for use with general offenders. This measure includes 130 items that assess an individual's static and dynamic risk, as well as strengths or protective factors. An overall risk index is calculated which involves subtracting the protective scale from the summed risk scales. Initial validation was completed on a sample of 162 general male offenders who were being released to a half-way house setting. Reliability indices suggested that the IORNS had sufficient internal consistency (α ranging from .51 to .91;Miller, 2006). Further the IORNS demonstrated concurrent validity with the LSI-R's total risk ($r = .45$, $p < .01$) score and was able to differentiate between offenders who were sent back to a correctional facility during follow up compared to those offenders who did not recidivate. Specifically, offenders who were sent back to a correctional facility twice during the 15 month follow up demonstrated significantly higher overall risk scores and dynamic needs ($t(116) = 2.38$, $p = .02$) as well as significantly fewer protective factors ($t(116) = 1.96$, $p = .05$) as compared to offenders who were not sent back to the correctional facility multiple times throughout the follow up.

Design and implementation of the DRAOR

The Dynamic Risk Assessment for Offender Re-entry (DRAOR; Serin, 2007; Serin et al., 2010) is a SPJ instrument that considers Stable, Acute, and Protective factors. The three domains have a demonstrated empirical relationship with increased risk of reoffending (Stable and Acute factors) and with desistance from crime (Protective factors). The DRAOR was developed to assist probation and parole officers in the assessment, and reassessment, of their clients' circumstances as they relate to the supervision process. The DRAOR provides officers the opportunity to assess their client at every supervision contact and make recommendations for

revised case planning and risk management strategies, as required. The DRAOR is designed to both assess risk, and to effectively manage risk. Therefore, the variables that are considered in the DRAOR assessment must not only demonstrate that they are dynamic risk factors, but also that risk is reduced when the factors are successfully changed (Hanson & Harris, 2000). As indicated previously, these variables may be further classified as causal dynamic risk factors if they demonstrate temporal precedence and increase the overall probability of reoffence, change as a result of intervention or sporadically, and predict changes in the likelihood of recidivism when altered (Kraemer et al., 1997). The inclusion of protective factors in the DRAOR provides the opportunity to develop an understanding of the internal and external mechanisms that potentially support the offender during the process of desistance.

Each item on the DRAOR is scored along a 3-point scale (0-2). For Stable and Acute factors, a score of 0 is indicated when the offender does not currently possess the risk factor. A score of 2 suggests that the particular risk factor is a definite problem for the offender. A score of 1 is assigned if the variable demonstrates a slight problem, or if it is not clear based on the information the officer has gathered. For the Protective scale a score of 0 indicates that the particular item is not protective for the offender whereas a score of 2 indicates that the item is definitely an asset. A score of 1 is used to indicate that the item could be a potential asset, or that there is not enough information to make a definitive selection. For research purposes a total score is calculated by summing the Acute and Stable scales and subtracting the Protective scale, however in practice, a total score for the DRAOR is not calculated. Rather, items in each domain are totalled to provide a summary of potential problem areas for community supervision officers to address. The DRAOR also includes risk scenarios whereby the officer attempts to identify which offender outcomes are plausible based on what is known about the offender at this time

(considering the DRAOR scores, and past criminal behaviour). Scenario planning is then used to inform case planning, including altering the level of supervision and intervention or management strategies.

Stable risk factors. Stable risk factors are those factors that have the ability to change, but the change is likely to be gradual. There are six variables considered under this domain related to peer associations, attitudes towards authority, impulse control, problem-solving, sense of entitlement, and attachment with others.

Acute risk factors. Acute dynamic risk factors can change rapidly (minutes, hours, days), and it is suggested that increases in these variables may indicate that reoffending is imminent (Hanson & Harris, 2000). The DRAOR measures seven acute risk factors including substance abuse, anger, opportunity for crime, negative mood, employment, interpersonal relationships, and living situation. This subscale reflects proximal indicators of risk state as described by Douglas and Skeem (2005) and answers the important question of when an offender might reoffend.

Protective factors. Protective factors are factors that potentially mitigate the probability of responding to at-risk situations with criminal behaviour. Protective factors are comprised of both internal (e.g. prosocial identity) and external (e.g. social support) strengths that can help an offender reduce their risk of reoffending. The protective factors that are assessed in the DRAOR include responsiveness to advice, prosocial identity, high expectations, cost/benefits, social support, and social control. These protective factors represent factors that are not merely the absence of risk, but rather positive attributes that protect or buffer the individual from potentially risky situations. It is believed that the more protective factors that one demonstrates, the greater the likelihood that they will be able to avoid the problematic behaviours. Of note, there was

considerable item overlap between the DRAOR Protective scale and the items that were examined by Ullrich and Coid's (2011) research which paralleled the development of the scale.

Initial findings with the DRAOR

The DRAOR has recently been implemented in New Zealand and has been tested in various jurisdictions throughout the United States. As a result, data regarding the psychometric properties of the DRAOR are accumulating. To date, the DRAOR has been administered to 4,049 offenders, and has been utilized to predict recidivism among general offenders (Hanby, 2013; Tamatea & Wilson, 2009), high risk offenders (Yesberg, Polaschek, & Serin, 2013), and sex offenders (Smeth, 2013). A brief summary of the results from this work follows, with particular emphasis on the preliminary psychometrics of the DRAOR.

Reliability. Among the small sample of probationers that Tamatea and Wilson (2009) examined, the DRAOR domain scores were found to be normally distributed and also demonstrated change throughout the supervision contact. In a more comprehensive validation whereby DRAOR assessments were examined for 3,498 offenders the internal consistency for the DRAOR domains was found to be acceptable for the Stable (α = .81) and Protective scales (α = .82), but the Acute scale demonstrated poor internal consistency (α =.62) (Hanby, 2013). Among a sample of high risk male offenders (Yesberg et al., 2013) the average total score for the stable items was 7.20 (*SD*=2.26) out of a possible score of 12, while the average total score for the acute items was 6.49 (*SD*=2.40) out of a possible score of 14. The average total score for the protective subscale was 5.51 (*SD*=2.18) out of a possible score of 12. The results suggested that offenders in this sample were significantly more likely to have stable risk factors present than acute risk factors or protective factors (Yesberg et al., 2013).

Validity. As an initial validation the DRAOR was administered to a small sample (n = 59) of New Zealand probationers (Tamatea & Wilson, 2009). Results suggested that that the Protective scale scores were significantly negatively correlated (r = -.33) with a measure of static risk (RoC*RoI), indicating that having a range of protective factors was associated with lower levels of risk.

Both the Stable and the Acute scores were significantly related to each other (r =.52) indicating that these subscales are associated with dynamic risk. Furthermore, the Protective scale revealed an inverse relationship with both Stable (r = -.33) and Acute (r = -.41) scores, suggesting that the Protective scale appeared to measure factors that were not related to dynamic risk or a measure of static risk. An independent samples t-test was utilized to examine any differences between offenders who had been revoked while on supervision, and those who successfully completed their supervision (termed desisters) at the time of data collection. Results indicated that the two groups significantly differed on the Protective Scale as well as on the measure of static risk (RoC*Rol). Those offenders who desisted from crime (n = 27) had higher mean scores on the Protective Scale as compared to those offenders who were classified as recidivists (n = 32).

Results from the larger sample of New Zealand offenders (Hanby, 2013) provided further support that the DRAOR is a valid measure of offender risk to reoffend. Results indicated that the DRAOR demonstrated good convergent validity with a measure of static risk (RoC*RoI). Both the score at initial assessment and the most recent assessment (before reoffence or the conclusion of the study) demonstrated moderate positive correlations with static risk, r = .32 and r = .37, respectively.

A sample of 299 high risk male offenders in New Zealand released from prison onto community supervision served as a further validation of the DRAOR (Yesberg et al., 2013). A series of correlations suggested that the DRAOR subscales and total score were not significantly related to static risk. However, the subscales and the DRAOR total were significantly related to the Violence Risk Scale (a measure that combines static and dynamic risk factors) and the Release Proposal Feasibility Assessment Revised (a measure that informs decision making regarding offender's level of preparedness for release). The finding that the Stable and Acute scales were not related to static risk instruments is inconsistent with the findings by Tamatea and Wilson (2009) although the Protective scale and the DRAOR total score did demonstrate a significant relationship with measures of static and dynamic risk. Analyzing only high risk offenders reduced variance among the DRAOR scales which could potentially explain the lack of a significant relationship with indices of static risk.

The DRAOR was also administered to a sample of 193 male sex offenders to evaluate whether dynamic risk factors contribute to the prediction of recidivism alongside static factors. Results indicated that the DRAOR total score and risk scales demonstrated convergent validity (r = .26) with a measure of static risk for sex offenders (Static 99-R).

Structure of the DRAOR. The structure of the DRAOR was developed to have three theoretically meaningful domains (Acute, Stable, and Protective scales). In an initial investigation of the structure of the DRAOR, a Principal Components Analysis (PCA) suggested that a four-component solution provided the best overall fit, explaining 51.3% of the variance (Yesberg et al., 2013). The four components were labelled Protective, Stable, Internal Acute, and External Acute. Results demonstrated that both DRAOR models were not correlated with a static measure of risk (RoC*RoI). The Protective scale was significantly inversely related to static risk

for violence as measured by the static subscale of the Violence Risk Scale (VRS). Other dynamic measures (VRS dynamic total and the RPFA-R) were significantly correlated with all DRAOR subscale scores for both the 3 and 4 factor solutions as well as the DRAOR total score. These results suggested that the stable and acute subscales from the original three-factor DRAOR structure and the new four-component solution were related to other dynamic risk measures but not to static risk instruments. However, the Protective scale demonstrated a relationship with both static and dynamic risk assessments.

The structure of the DRAOR was also investigated by Hanby (2013) using baseline DRAOR scores and, similarly, results suggested that three factors be retained which explained 38.2% of the variance. The three factors contained 17 of the 19 original DRAOR items with Interpersonal Relationships and Employment being dropped from the model. The structure matrix suggested that the Stable and Acute items were loading onto more than one factor resulting in strong inter-correlations among the factors. The *Mostly Stable* and *Mostly Acute* factors had a medium correlation of .49. The *Protective Factor* had medium to large negative correlations with *Mostly Stable* (r = -.39) and *Mostly Acute* (r = -.66). Of the three factors that comprised the model, the *Mostly Acute* factors accounted for the most variance (29.9%).

The stability of the factor solution was examined using the generalized least squares extraction method. The model that was extracted resulted in 3 factors but the structure of these 3 factors differed from the results of the principal factors extraction. A similar amount of variance was accounted for by the model (38.6%), but most of the variance was accounted for by the *Stable* (30.0%) factor. The three factors that were extracted were defined as *Stable, Mostly Stable,* and *Mixed Stable/Acute*. Similar to the previous model, the factors demonstrated medium to large inter-correlations.

The middle and final DRAOR assessment scores were utilized to test the stability of these three proposed models using Confirmatory Factor Analysis. Various indices of model evaluation suggested that structure sufficiently fit the data, with Model # 2 (derived from principal factors extraction) outperforming the other models. Similar results were obtained for the last DRAOR assessment however; Model #2 demonstrated the best fit for the data. The psychometric properties and the results regarding predictive accuracy suggest that the original DRAOR and its subscales appear to be superior to the alternative models developed through factor analysis (Hanby, 2013).

Predictive utility. To examine the predictive accuracy of the DRAOR Hanby (2013) utilized the most recent DRAOR assessment (assessment most proximal to the recidivism event). The DRAOR and its subscales consistently predicted the reconviction outcomes to varying degrees, with small to medium effect sizes. Larger effect sizes were observed for reconvictions than criminal reconvictions, with *AUC* values ranging from .66 to .72 for reconvictions (i.e. being reconvicted based on a violation) and .62 to .67 for criminal reconvictions in the overall sample. The effect sizes for a subsample of Maori offenders were slightly lower, with *AUC* values ranging from .65 to .70 for reconvictions and .61 to .66 for criminal reconvictions. Results indicated that the predictive accuracy of the original DRAOR total score was slightly higher than the revised DRAOR (Model 2) total score for each of the samples and outcome measures.

The DRAOR was also examined to determine if it could incrementally add (above static risk) to the prediction of recidivism. Results suggested that for the prediction of both reconvictions and criminal reconvictions, the DRAOR contributed to the prediction above and beyond the contribution of static risk. For the prediction of all reconvictions the combined static/dynamic model demonstrated and *AUC* of .77. This combined model also produced an

AUC of .74 for the prediction of criminal reconvictions. Both predictions demonstrated improvements over the static only model. Scores on the Protective subscale were expected to predict desistance from crime, but results were unable to support this hypothesis.

In an evaluation of the DRAOR among a sample of high risk male offenders in New Zealand, Yesberg and colleagues (2013) found that the Protective scale of the DRAOR was able to predict breaches of parole, new convictions, and reimprisonment for offenders over a 6 month period. Results also suggested that scores on the Stable subscale predicted reconvictions, and the Acute scale predicted reconvictions and reimprisonment. The DRAOR total score was able to significantly predict an offender incurring a new conviction and being reimprisoned. The DRAOR total score also incrementally added to the prediction of reconvictions, making significant improvements over the model that only considered static risk. However, results did indicate that the DRAOR was unable to add incrementally to the prediction of reimprisonment. The authors note that the lack of predictive validity for reimprisonment may be due to relatively low base rates which impact the ability to statistically detect differences over such a short follow up period. However, these initial results provide support for the continued use of the DRAOR for use with the prediction of recidivistic events.

Lastly, the utility of the DRAOR was recently examined among a sample of 193 male sex offenders on community supervision in the state of Iowa (Smeth, 2013). Due to low base rates for sexual and violent recidivism, the outcome of interest was technical violations. Results indicated that all DRAOR domains and total score significantly predicted parole violations (*AUC*s ranging from .61 to .69). Additionally, results from a Cox regression survival analysis revealed that those individuals with higher scores on the risk scales of the DRAOR failed at a faster rate than those with lower scores on the DRAOR. Lastly, higher scores on the DRAOR

Protective scale were related to an increase in survival time, with recidivism being decreased by 12% for every 1 point increase in the Protective score.

Overall, initial results suggest that the DRAOR is psychometrically sound, and that it is sufficient at predicting various offender outcomes (i.e. technical violations, general recidivism, violent recidivism). Further testing the DRAOR among regionally diverse samples is warranted in order to conclude that the scale is able to be utilized with various offender populations worldwide.

Current Study

With an emphasis on dynamic risk factors, and the inclusion of protective factors, the DRAOR has the potential to inform case-level decisions regarding individual offenders and improve community supervision practices. Thus, one of the goals of this study is to further our understanding of offender assessment and contribute to the growing literature surrounding evidence based practices. Although initial results involving the DRAOR suggest that it is a valid and reliable measure, much of these conclusions have been based on data from New Zealand. The purpose of this study is to provide a validation of the DRAOR with general offenders in the United States. An archival dataset with a sample of 1,963 probationers and parolees, who were administered the DRAOR by trained supervision officers, will be utilized for the current study. This study will also investigate the factor structure of the DRAOR to determine if the current structure is appropriate for use with U.S. parolees.

To evaluate the predictive accuracy of the DRAOR various offender outcomes will be considered. Specifically, data involving technical violations, general recidivism, and violent recidivism will be analyzed for offenders with a variable follow up, contingent on time spent in the community. The study's time period ranges from March 2011 to November, 2013.

Comparisons between those who reoffended and those who successfully remained on community supervision will be conducted to examine any differences across the DRAOR subscales and total score. It is anticipated that offenders who reoffended will demonstrate higher Stable, Acute, and Total scores, as well as lower Protective sores relative to those offenders who did not record a recidivistic event during the study. It is also of interest to examine whether the DRAOR is differentially predictive according to levels of static risk. Specific hypotheses pertaining to study's various objectives are outlined below.

Hypotheses:

Hypothesis 1: The DRAOR will demonstrate satisfactory psychometric properties (e.g., factor structure, inter-item correlations, item distributions, and internal consistency).

Hypothesis 2: It is hypothesized that those who reoffend will demonstrate increased scores on the Stable, Acute and total DRAOR scores as compared to those who remained crime free, who are expected to score lower on the risk scales and higher on the Protective scale.

Hypothesis 3: It is anticipated that the DRAOR risk scales and total score will successfully predict recidivism. Similarly, increased protective factors will predict successful (i.e. crime-free) community supervision.

Hypothesis 4: The DRAOR will be able to predict time to recidivism (i.e. technical violations, general recidivism, and violent recidivism), with those demonstrating higher risk indicators (i.e. higher scores on DRAOR risk and total scores) failing on community supervision more rapidly than those with lower DRAOR scores.

Hypothesis 5: The predictive validity of the DRAOR will be enhanced at higher levels of static risk (i.e. Iowa Risk Assessment) compared to moderate and low levels of static risk.

Hypothesis 6: There will be a stronger effect for protective factors at higher levels of dynamic risk.

Method

Participants

Selection procedure. All offenders serving community supervision orders in the 5th District in the state of Iowa were eligible to be included in the study. Each offender's DRAOR scores were compiled electronically and provided for future examination. Data were compiled for 1,963 offenders who allegedly had at least one DRAOR assessment completed. A subset of these offenders (n = 38) had multiple, independent, supervisions which ultimately led to having DRAOR data for 2,001 supervisions. Initial investigation suggested that there was widespread missing data across the DRAOR assessments (40.7%) which led to the development of two criteria to strengthen the integrity of the current study. Firstly, in order ensure that scores across the DRAOR domains accurately reflect what was recorded only those assessments that have no missing data are considered for further analyses. It appeared that offenders who began their supervision term closer to the date of implementation (i.e. March 2011) were likely to have missing data (see Table 1). Further, as seen in Table 2, comparisons made between those offenders with and without missing data suggested that offenders with no missing DRAOR data were significantly younger and started their supervision period more recently than those offenders with missing DRAOR data. These findings confirmed the decision to exclude these cases from future analyses.

Table 1

Missing Data on the DRAOR by Year

Year	Missing *n*	(%)	Total *n*
2004	1	100.00	1
2006	1	50.00	2
2007	3	75.00	4
2008	8	80.00	10
2009	25	60.97	41
2010	86	67.71	127
2011	187	58.25	321
2012	305	35.18	867
2013	199	31.69	628
Total	815	40.73	2001

Note: Total *n* represents the total number of offenders who started their supervision for that given year.

Table 2

Comparisons Among Those Offenders With and Without Missing Data

Variable	No missing data *M* (*SD*)	Missing data *M* (*SD*)	*t*	*df*
Age	31.95 (10.74)	33.19 (12.13)	-2.35*	1606.75
Static Risk	13.67 (4.41)	13.75 (5.12)	-0.31	1086.37
Supervision start (months)	14.57 (10.15)	20.64 (13.01)	-11.29***	1999
Time to assessment	221.18 (274.53)	219.11 (291.46)	0.16	1999

Note: 954 offenders with no missing DRAOR data had a static risk score as did 580 offenders who had missing DRAOR data.
* $p < .05$, *** $p < .001$

This subset of offenders was then examined to determine when the DRAOR assessment was completed in relation to their supervision start date. In order to accurately capture the initial stages of supervision, in which the offender is at a heightened state of vulnerability to future crime (Brown, St. Amand, & Zamble, 2009), a decision was made to only include assessments occurring within the first 60 days. A similar pattern emerged when analyzing the impact of this criterion, whereby the closer the supervision start date was to the date of DRAOR implementation, the less likely the first assessment was completed in the first 60 days (see Table 3). Officers began to utilize the DRAOR with all of their clients during each supervision session, which resulted in administering the DRAOR to offenders who had been on community

supervision for an extended period of time. Since these offenders are likely at a different stage of their supervision order (i.e. have successfully remained on supervision) they represent a distinct subsample of offenders who could potentially impact the results. By applying this criterion, the sample was further reduced to a final sample of 391.

Table 3

Offenders Assessed on the DRAOR within 60 Days by Year That Supervision Began

Year	*n* assessed within 60 days	%	Total *n*
2006	0	0.00	1
2007	0	0.00	1
2008	0	0.00	2
2009	0	0.00	16
2010	0	0.00	41
2011	2	1.49	134
2012	157	27.94	562
2013	232	54.08	429
Total	391	32.97	1186

Note: Total *n* represents the total number of offenders who started their supervision for that given year. Sample reflects only those offenders who do not have missing data on DRAOR scale.

The characteristics of the current sample were compared to the overall population of offenders serving community supervision sentences in the state of Iowa to assess the representativeness of the sample (see Table 4). Descriptive comparisons between the current sample and the overall sample of offenders on community supervision in Iowa revealed definitive differences across gender, race, age, and supervision status. Although these differences were noted in order to consider sample representativeness, further analyses were not completed given sample sizes. Hence, gender and ethnicity were not examined in terms of differential effects of the DRAOR scores. The average level of supervision according to the classification of scores on the Iowa Risk Assessment is intensive (M = 13.82, SD = 4.77). Participants ranged in age from 16 to 85 with an average age of 32.43 (SD = 11.58). The vast majority (n = 285, 72.89 %) of the sample had either completed their GED or received their high school diploma. The

majority (62.7%) of participants indicated they were single, 15.9 % of the sample had been divorced, and 15.6% indicated they were either married or in a common law relationship at the time of release. The remaining offenders were either separated (3.3%) widowed (0.3%), or did not indicate their relationship status (2.3%).

Table 4

Sample Representativeness: Study Sample (n = 391) vs. Iowa's Community Corrections Population as of 06/30/2013 (N =30,297)

Variable	Sample % (*n*)	Iowa's Offender Population % (*n*)
Gender		
Male	79.5 (311)	74.2 (22,484)
Female	20.5 (80)	25.6 (7,762)
Unknown	0.0 (0)	0.00 (51)
Race		
African American	30.9 (121)	15.0 (4,529)
White	68.5 (268)	77.5 (23,468)
American Indian	0.5 (2)	1.1 (317)
Asian or Pacific Islander	0.0 (0)	1.1 (317)
Hispanic	3.3 (13)	5.0 (1,496)
Unknown	0.0 (0)	0.5 (170)
Supervision status		
Parole	26.1 (102)	12.6 (3,825)
Probation	44.2 (173)	75.0 (22,711)
Work Release	19.7 (77)	5.5 (1,654)
Pretrial Release	3.6 (14)	5.1 (1,549)
Special Sentence	6.4 (25)	1.8 (543)
Age		
Under 31	50.6 (198)	47.8 (14,479)
31-50	41.7 (163)	41.0 (12,434)
Over 50	7.7 (30)	11.2 (3,384)

Note: data on race and ethnicity were separate for the current study although to allow for comparisons with Iowa's sample ethnicity was included under race.

For a large portion (34.5%) of the sample the most serious offence committed was classified as violent (e.g. assault). The remainder of the sample had committed drug offences (26.9%), property offences (21%), or public order offences (45%) as their most serious offence.

For offenders who were on community supervision for the first time, this offence represents their index crime that led to the current supervision, whereas for offenders who have been repeatedly involved in the correctional system, this offence could have occurred previously and as a result, did not lead to the current supervision.

Procedure

Community supervision officers were originally involved in a pilot evaluation of the DRAOR. During this project, officers received one day of in class training by Dr. Ralph Serin (scale developer) on August 25, 2010 which emphasized the general literature of dynamic risk, the composition of the DRAOR, as well as scoring procedures. An advisory group was created among the officers to ensure that others received support when required. Dr. Serin was also available to the advisory group to address any issues as they arose. Officers began scoring the DRAOR during their supervision sessions once they received the training. The data were recorded in the form of file notes which were then provided to facilitate data analysis.

All data collection and coding were completed by the staff of Iowa Department of Corrections. An electronic version of all data was then provided which was restructured to increase the suitability of the data for the current study. Two undergraduate research assistants were utilized to assist with the restructuring process. The accuracy of their recoding was consistently examined to ensure that information that was transferred was indeed the same as what was originally recorded by the community supervision officers[1]. Examining the assessments in this manner suggested that there were no errors in the restructuring of the information by the research assistants.

[1] An assessment was chosen at random (approximately every 20) to check for errors with the original information provided from Iowa Department of Corrections.

Typically the information recorded in the initial document was restructured verbatim, although there were a few exceptions. When officers scored the DRAOR they often also included a description of the offenders' experiences in relation to the relevant item. When these descriptions clearly indicated that the scoring was incorrect (e.g. offender has plenty of support from family and friends, but prosocial support was scored as 0) then the scoring for that particular item was reversed. Issues particularly surfaced with the Protective subscale scoring, presumably as a result of the reverse scoring. A total of 19 assessments had a score on one or more item that was changed as a result of the scoring description recorded by the assessing officer.

Measures

Dynamic Risk Assessment for Offender Re-entry. The DRAOR is a clinical rating scale that considers Stable, Acute, and Protective factors. The 3 domains provide community supervision officers with a structured outline to examine an offender's current experiences on a consistent basis. All of the DRAOR factors are scored on a three-point scale. Stable factors consist of risk factors that gradually change (e.g. antisocial attitudes), while Acute factors (e.g. anger) represent risk factors that can change rapidly. Each Stable and Acute factor is rated as "no problem", a "slight problem" or a "definite problem". The Protective domain addresses factors such as prosocial identity and can be scored as a "not protective", a "slight/possible asset", or "definite asset". For the purposes of examining the predictive ability of the DRAOR as a whole, a total score is created by summing the scores of domain. Total scores can range from -12 to 26, with lower scores indicative of lower risk and greater protective mechanisms, and higher scores suggesting higher overall risk and lower protective factors.

The DRAOR also includes risk scenarios that provide probation officers with recommended problematic situations for their clients that might lead to reoffending.

Additionally, officers are able to identify their level of concern for imminent reoffence or violation of supervision conditions on a scale of 1 to 6. It is recommended that supervising officers administer the DRAOR at each supervision session (i.e. typically monthly) to ensure that any changes in the offender's circumstances are captured.

Iowa Parole Risk Assessment. The Iowa Parole Risk assessment is a static risk scale that assesses a series of historical variables to arrive at a risk estimate of future violence risk resulting in a conviction. Offender's current age, age at first arrest, prior convictions, alcohol and drug problems are examples of the static variables that are considered. Additionally, the offender's relationships and employment history are considered in the calculation of the total score. There are a total of 13 items, which are summed to reach a total score ranging from -5 to 25. Two scores are calculated which represent the risk of committing a violent offence (labelled violence score) and victimization risk which are new property offences or violent crimes. The risk level directly informs the recommended level of supervision (e.g. high) and allows the officer to override the results if there are extraneous variables to consider (e.g. case plan indicates high needs). Results of a thorough validation including 2,006 female offenders and 1,961 male offenders have suggested that the victimization score is a valid predictor of any new violent, property, or drug crime (*AUC* = .68), and any new crime or revocation (*AUC* = .66) for male offenders (Prell, 2013). The victimization score performed equally as well for female offenders, predicting any new violent, property, or drug crime (*AUC* = .66), and any new crime or revocation (*AUC* = .61). The violence score was also found to be predictive of violent offences for both female and male offenders (*AUC*s of .69 and .71 respectively). Although not the primary focus of this study, this measure was included to facilitate a moderation analysis to

examine whether dynamic risk factors demonstrate an increased effect at higher levels of static risk.

Outcome data

For this study there were four possible recidivism events that could have occurred: technical violations, general recidivism, violent recidivism, and any recidivism (i.e. technical violations or a rearrest). Technical violations were defined as either breaches of supervision restrictions (e.g. abstaining from alcohol or drugs) or facility misconducts if the offender was serving their community supervision sentence in a community residential facility (i.e. half-way house). General recidivism included all rearrests for drug related, driving offences, property offences, or administrative (e.g. tax evasion) crimes. Violent reoffending consisted of any arrest for domestic abuse, assault, robbery, or murder. Recidivism was coded based on rearrest information contained in the Iowa Corrections Offender Network (ICON), which tracks any statewide criminal activity. Time at risk was calculated for each of the outcome variables based on the time of the supervision start and the respective recidivism event. For those offenders with no recidivism data, time at risk was calculated to the end of the follow-up period (November 19, 2013).

Demographic information, such as age, gender, and ethnicity was also gathered from ICON. Further, the offender's most serious crime was obtained along with the other risk indices (e.g. Iowa Parole Risk Assessment) when available.

Data Analysis

Once the data were restructured in a manner that facilitated analyses, SPSS 19.0 was used to organize, screen, and run the primary analyses. Mplus 6.0 (Muthen & Muthen, 2010) was used for exploratory factor analysis, along with a supplemental analysis (i.e. parallel analysis) completed using FACTOR 9.2 (Lorenzo-Seva & Ferrando, 2013).

Psychometrics

In an effort to validate the use of the DRAOR on a sample of offenders under community supervision in the United States several various indices of reliability and validity were examined. Chronbach's alpha was used to assess the internal consistency of each of the DRAOR subscales. Chronbach's alpha usually ranges between 0 and 1; the closer the coefficient is to 1, the greater the internal consistency of the measure. While there has been some debate over what an acceptable Cronbach's alpha level is, generally .80 is the recommended guideline to make claims that the scale is reliable. Further, inter-item correlations and score distributions were examined to assess the DRAOR's reliability. Based on previous research (Hanby, 2013) it is expected that the individual items will demonstrate inter-item correlations of at least .30 with the DRAOR total score.

Factor structure

In order to assess the appropriateness of the structure of the DRAOR for use in U.S. offender samples, an exploratory factor analysis (EFA) was performed. An EFA is used to summarize data by grouping variables into subsets that are relatively independent of one another (Tabachnick & Fidell, 2013). EFA only includes shared variance in the factor solution which avoids inflating the estimates of variance accounted for (Costello & Osborne, 2005). EFA is most typically utilized in the early stages of research where it provides an opportunity to generate hypotheses as to what processes underlie the factors that are apparent (Tabachnick & Fidell, 2013). The use of EFA was chosen over principal components analysis (PCA) as the latter is typically used when there is no underlying theory about which variables should be associated with which factors (Fabrigar, Wegener, MacCallum, and Strahan, 1999). Additionally, EFA considers error variance and provides a more realistic model of the structure of correlations.

To provide an estimate of the underlying latent factors an EFA analyzes a correlation matrix; which, in the social sciences is typically a Pearson Product-Moment correlation matrix. Due to the ordinal nature of the items included in the EFA, utilizing a matrix of polychoric correlations is the recommended approach (Flora & Curran, 2004; Holgado-Tello, Chacón–Moscoso, Barbero–García, & Vila-Abad, 2010; LaBrish, 2011). The reduced variability as a result of the ordinal level of measurement is problematic for Pearson Product-Moment correlations and can lead to biased estimates and underestimated factor loadings, particularly when the data are skewed (Brown, 2006; Flora & Curran, 2004).

Polychoric correlations estimate the relationship between two theorized normally distributed, continuous latent variables based on two observed ordinal variables (Flora & Curran, 2004; LaBrish, 2011). Simulation studies have demonstrated that polychoric correlations are more consistent and robust correlation estimators for ordinal data (Holgado-Tello et al., 2010; LaBrish, 2011).

Factor extraction. Factors were extracted utilizing the weighted least square (WLSMV) method, which is recommended by Muthén and Muthén (2010) for exploratory factor analysis of ordinal data. The WLSMV estimator technique has consistently demonstrated robustness to violations of normality and relatively small sample sizes (Flora & Curran, 2004; Brown, 2006). Due to the expected correlations between factors that are extracted, an oblique rotation (Geomin) was utilized (Costello & Osborne, 2005).

Factor retention. In an effort to be confident in the number of factors retained, various indices used for factor retention were considered including analyzing scree plots, examining eigenvalues greater than 1 (Kaiser criterion) and through the use of parallel analysis. Although Costello and Osborne (2005) argue that utilizing the Kaiser criterion can lead to inaccurate

findings, Fabrigar et al. (1999) recommend considering all indices of factor retention. Parallel analysis involves comparing the eigenvalues obtained from the sample data to eigenvalues that one would expect to obtain from random data (Hayton, Allen, & Scarpello, 2004). Eigenvalues from the sample data that are greater than the randomly generated eigenvalues represent those factors that should be retained. The use of parallel analysis with ordinal level EFA has been debated. Some have argued that the Pearson Product-Moment correlation matrix should be utilized, whereas others have recommended utilizing the polychoric matrix (Cho & Bandalos, 2009; Garrido, Abad, & Ponsoda, 2013; Timmerman & Lorenzo-Seva, 2011). Generally, simulation studies revealed that at null or moderate levels of skew, Pearson based parallel analysis and polychoric based parallel analysis yielded similar results. The strength of polychoric based parallel analysis typically emerged when items were largely skewed, when factor loadings were large, and when the sample size was 200 with 3-level items (Cho & Bandalos, 2009). Garrido and colleagues (2013) have proposed a variant of the original parallel analysis (Horn, 1965) which utilizes minimum rank factor analysis. These authors have found that this method has been marginally superior to the principal components extraction method used in parallel analysis and substantially more accurate than the principal axis factoring method of parallel analysis. Further Timmerman and Lorenzo-Seva (2011) found that this strategy led to more accurate factor solutions, specifically when utilizing the 95% threshold eigenvalues for comparison. As a result, parallel analysis based on minimum rank factor analysis (PA-MRFA) was utilized to compute eigenvalues at the 95% threshold for comparison with the obtained sample eigenvalues.

Factor structure fit. Once the optimal number of factors was determined, the overall fit of the factor structure was examined. Fit indices are recommended to be used as guidelines

(Schmitt, 2011) as there has been some debate, specifically in terms of cut-off for each index. The root mean square error of approximation (RMSEA) was used to assess the discrepancy of fit between the model and the data per model degree of freedom, adjusted for sample size of fit in the factor structure compared to a perfect factor structure (Tabachnick & Fidell, 2013). It is suggested that these values should not exceed .06 (Schmitt. 2011). The comparative fit index (CFI) was used to assess the factor structure relative to a baseline model where there are no relationships between items (Brown, 2006). Values greater than .95 are expected to represent a good fit. Lastly, the standardized root mean square error (SRMR) was considered which represents the average difference between the original correlations in the input matrix and the correlations predicted by the obtained factor structure. Generally, values less than .08 are indicative of acceptable fit. Fit indices for the obtained factor structure were compared to a more complex model (i.e. with one more factor) to examine whether the fit improves; Fabrigar et al. (1999) emphasize that there should be little improvement if the selected model represents the correct solution. It is important to note that much of the research on fit indices is based on their performance for EFAs conducted on Pearson correlations. Recently, LaBrish (2011) examined the accuracy of fit indices for EFAs based on polychoric correlations and determined that these were more accurate at identifying the correct factor solution than compared to indices based on Pearson correlations, particularly when factor loadings are high.

Factor loadings. To determine which items represent the factors that comprise the model, each item's factor loading was examined. Typically, factor loadings of .30 to .40 or greater are said to load onto a particular factor (Tabachnick & Fiddell, 2013). Additionally, standardized factor loadings for each item were assessed to confirm that the items load on the expected factor. The significance of the factor loading was determined by testing whether the

factor loading significantly differed from zero. A procedure that corrects for any potential vulnerability to Type 1 errors was utilized (Schmitt, 2011) whereby an appropriate alpha level is calculated. A *Z*-score corresponding to the corrected alpha level was then used as the critical point to determine the significance of the factor loadings.

Prediction

To assess the predictive accuracy of the subscales of the DRAOR and total score, Receiver Operating Characteristic (ROC) analysis, and area under the curve (*AUC*) statistics were calculated. An *AUC* is used to determine if an instrument is predictive, better than chance, of an outcome; this is accomplished by examining the differences between recidivists and non-recidivists. Thus, an *AUC* represents the probability that a score on a measure drawn at random from one sample (i.e. scores of recidivists) is higher than a score drawn at random from another sample (i.e. scores of nonrecidivists). For this study, the DRAOR was analyzed to determine if it can predict various recidivism events, including technical violations, general criminal recidivism, and serious (violent) criminal recidivism. *AUC*s range from .00 to 1.00 with .50 indicating that the prediction is no better than chance; an *AUC* of .00 indicates a perfect negative relationship, and an *AUC* of 1.00 indicates a perfect positive relationship. *AUC*s are of substantial utility in research that examines outcomes with infrequent occurrences, as the *AUC* is largely unaffected by base rates (Andrews & Bonta, 2010). In the forensic literature Rice and Harris (2005) have recommended the following interpretations of the magnitude of *AUC*s: .539 is considered low, .639 is a moderate relationship, and .714 represents a high relationship. To compare if one subscale is significantly more accurate in predicting a recidivism outcome, the 95% confidence intervals will be compared. When these confidence intervals do not overlap it suggests that there may be a significant difference between the *AUC*s. This can be further supported by the use of

the Delong test which allows for statistical comparisons through the calculation of a standard error of the difference (DeLong, DeLong, & Clark-Pearson, 1988).

Time to recidivism was examined through the use of Cox regression survival analysis techniques with three separate models calculated for each outcome of interest (technical violations, reoffence, and any recidivism). Cox regression is a semi parametric test that models the relation between predictor variables and an event (recidivism) while accounting for time to the occurrence of the event. This approach allows multiple predictors to be measured simultaneously in order to determine their independent and unique contributions to the outcome variable (Tabachnick & Fidell, 2013). This analysis was chosen over logistic regression as Cox regression survival analysis is able to incorporate variable follow-up times and sample censoring (Brown et al., 2009; Tabachnick & Fidell, 2013). Cox regression analyses produce a hazard ratio, which represents the predicted change in the hazard (i.e. recidivism) for a unit increase in the predictor (i.e. Stable risk, Acute risk, Protective factors, Total score).

In order to examine the potential differential impact of dynamic risk across stable risk domains, a moderated Cox regression survival analysis was performed. The Iowa Risk Assessment was utilized as a measure of static risk which measures an offender's risk across various domains (i.e. criminal history, criminal associates, age at first offence, etc.). Both the static measure and the DRAOR total were entered in an initial model to test the independent effects on recidivism. In the second block of the analyses a cross product of static risk and the DRAOR total score was entered to examine if the prediction of recidivism varies across the levels of static risk (i.e. low, moderate, high).

Similarly, a moderated Cox regression survival analysis was performed to examine the impact of protective factors at various levels of dynamic risk. It is of interest to determine if the

effect of protective factors is strengthened at higher levels of dynamic risk, rather than a lower levels of risk (e.g. protective factors may be more salient for offenders who demonstrate high levels of risk as compared to lower levels of risk). To test for the independent effects of risk and protective factors (i.e. main effects) both factors will be entered into the first block, while the interaction term of Risk x Protective will be added to the second block. The interaction term was not centered, since zero is a meaningful score on the DRAOR and is not necessary when such is the case (Cohen, Cohen, West, & Aiken, 2003). It was anticipated that a buffering interaction would exist, whereby the two predictors (i.e. protective and risk scores) will have opposite signs, suggesting that protective factors will mitigate the risk factors (Cohen et al., 2003).

Results

Data management

Descriptive information for DRAOR items and subscales is presented in Table 5. All scores across the DRAOR items and subscales were in the valid range. Given that the presence of missing data across any items resulted in being excluded from analyses there are no additional issues with missing data.

Variables were examined for linearity, homoscedasticity, normality, univariate and multivariate outliers, and multicolinearity. These assumptions were examined across the DRAOR subscales as opposed to the individual items as these were the scores that would be utilized in future analyses. An analysis of box plots and standardized z-scores for the DRAOR subscales suggested that there were no univariate outliers. Inspection of bivariate scatterplots suggested the presence of linear relationships for each combination of the variables. The assumption of homoscedasticity also appears to be supported with roughly the same variability in scores for each variable at all values of the other variables.

Table 5

Descriptive Information Across DRAOR Items and Subscales

Variable	Range	*M*	*SD*
DRAOR total	-12 – 25	5.83	6.85
Stable Total	0 – 12	5.51	2.70
Peer association	0 – 2	1.21	0.59
Attitudes toward authority	0 – 2	0.75	0.66
Impulse control	0 – 2	1.10	0.67
Problem solving	0 – 2	1.03	0.62
Sense of entitlement	0 – 2	0.68	0.67
Attachment to others	0 – 2	0.74	0.55
Acute Total	0 – 14	6.44	2.78
Substance use	0 – 2	0.99	0.79
Anger	0 – 2	0.72	0.73
Access to victims	0 – 2	0.74	0.68
Negative mood	0 – 2	0.72	0.64
Employment	0 – 2	1.26	0.83
Interpersonal relationships	0 – 2	1.07	0.65
Living situation	0 – 2	0.94	0.70
Protective Total	0 – 12	6.13	2.65
Responsive to advice	0 – 2	1.08	0.56
Prosocial identity	0 – 2	0.99	0.56
High expectations	0 – 2	1.11	0.62
Cost/benefits	0 – 2	1.04	0.59
Social support	0 – 2	1.01	0.57
Social control	0 – 2	0.89	0.58

Kolmogorov-Sminov's test of normality was performed on each of the variables to examine whether the values are normally distributed. Results of these tests suggested that all DRAOR variables depart from normality; however given the large sample size, obtaining significant results is not surprising. Rather than relying on formal tests, it is recommended to visually inspect the shape of the distribution when the sample size is large (Tabachnick & Fidell, 2013). An examination of the data (i.e. histograms, probability plots, skewness and kurtosis ratios) suggests that departures from normality are not vast. Using a conservative alpha level of

.001, all of the standardized skewness and kurtosis ratios were within the critical value of ± 3.29 (two-tailed test). Further, the data graphically represented a normal distribution.

The presence of multivariate outliers was examined through Mahalanobis' distance and influence values. Results indicated that one case exceeded the critical value of 18.467 ($df = 4$, $\alpha = .001$; Tabachnick & Fidell, 2013). Consideration of influence values (i.e. Cook's distance) suggested that there were no cases that would be considered outliers using this index (i.e. Cook's D < 1.00). As a result, the one case that surpassed the Mahalanobis' distance was retained in further analyses as indices of outliers failed to conclusively identify this case as a multivariate outlier.

All variables were evaluated for singularity and multicollinearity using bivariate correlations. Results indicated that there were no potential issues with multicollinearity as no pair of variables evidenced a perfect, or near perfect, relationship. The largest correlation was between the Stable and Acute risk scales (see Table 6).

Table 6

Inter-correlations Between DRAOR Subscales

	Acute Risk	Protective Factor
Stable Risk	.73***	-.53***
Acute Risk		-.49***

*** $p < .001$

Lastly, the proportionality of hazards assumption of Cox regression survival analysis was tested. This test assumes that the shape of the survival function is the same for all cases and all groups over time. Violation of this assumption signifies an interaction either between group membership and time, or between other covariates and time (Tabachnick & Fidell, 2013). This assumption was tested by examining the log minus the log plots of the hazard function. This assumption was not violated as survival curves were parallel and did not cross each other.

Psychometrics of the DRAOR

Hypothesis 1. The DRAOR will demonstrate sufficient psychometric properties (e.g., factor structure, inter-item correlations, item distributions, and internal consistency).

Exploratory factor analysis. An exploratory factor analysis was performed to empirically determine whether the original 19 item scores clustered as predicted on the Stable Risk, Acute Risk, and Protective Factors subscales. Typically in the social sciences, exploratory factor analysis is conducted through the examination of covariance matrices based on Pearson product moment correlations. However, when the level of measurement for each item is ordinal, Pearson product-moment correlations tend to reflect diminished relationships (Flora & Curran, 2004; Holgado-Tello, et al., 2010; LaBrish, 2011). These restricted correlations may lead to underestimated factor loadings and less accurate factor solutions (Brown, 2006; Holgado-Tello et al., 2010). The use of polychoric correlations with ordinal data has been purposed as an effective strategy to accurately capture the bivariate relationships present among these data. Polychoric correlations estimate the linear relationship between two unobserved (latent) continuous variables based on observed ordinal data (Flora & Curran, 2004). This technique has not been consistently utilized throughout the social sciences, so exploratory factor analyses were performed utilizing both the polychoric correlation matrix as well as a Pearson product-moment correlation matrix to allow for comparison between models, as well as with previous research.

The sample size of 391 was sufficient for generating reliable and replicable factors. According to the criteria outlined by Hutcheson and Sofroniou (1999) the current data were adequate for conducting factor analysis (Kaiser-Meyer Olkin measure of sample adequacy; KMO = .90). The ratio of participants to variables is also adequate at a ratio of 20:1.

A polychoric correlation matrix was examined to determine factorability and to check for any issues with multicollinearity and singularity. The matrix consisting of 19 items yielded 171

unique bivariate correlations ranging from .04 to .71. Of these, 111 were .30 or larger suggesting that these items are factorable. Further, Bartlett's test of sphericity was significant (χ^2 (df = 171) = 2638.9, p < .001) and the determinant of the R matrix (.001) suggested there were no issues with multicollinearity or singularity.

The initial model consisted of factors extracted via the weighted least square (WLSMV) method. The WLSMV estimator is the recommended factor extraction technique when utilizing ordinal data for exploratory factor analysis (Brown, 2006; Muthén and Muthén, 2010). Further, WLSMV has demonstrated to be robust against violations of normality, and perform well regardless of ceiling or floor effects with sample sizes as small as 200 (Brown, 2006).

As noted previously, to determine the appropriate number of factors to retain, the scree plot, Kaiser's criterion, and comparing randomly generated eigenvalues to the sample eigenvalues (i.e. parallel analysis) were considered. As displayed in Table 7, Kaiser's criterion suggested retaining five factors. It is recommended that Kaiser's criterion is generally accurate when there are less than 30 variables and communalities after extraction are greater than .7 when sample sizes are small (Field, 2005). Among these data, there are 19 variables, with a moderate sample size of 391, and with only 9 factor loadings surpassing .7. As a result, relying on Kaiser's criterion may produce and inaccurate solution. An analysis of the scree plot's point of inflexion suggested retaining either two or four factors, and the results of a parallel analysis (i.e. 500 random correlation matrices based on a normal distribution, with 391 participants and 19 variables) suggested that two factors be retained for the final solution. The application of parallel analysis with item level data has been debated, but there has been recent support for continued use, with results suggesting that parallel analysis based on polychoric correlations outperforms parallel analysis based on Pearson r correlations, particularly when the distribution of the items

is asymmetrical (Cho & Bandalos, 2009; Garrido et al., 2013; Timmerman & Lorenzo-Seva, 2011). Since Kaiser's criterion and the scree plot are subjective factor retention approaches, it was decided that the empirical method of parallel analysis would be given the most weight; therefore two factors were retained.

Table 7

Recommended Factors Based on Eigenvalues From Sample Correlation Matrix.

Factor	Initial eigenvalue
1	7.87
2	2.02
3	1.41
4	1.30
5	1.01
6	0.80*

Note * represents the point in which the eigenvalue is lower than the Kaiser criterion.

Model fit statistics were then utilized to examine the fit of the final factor structure. A two-factor model fit the data well, with a RMSEA of .08 (90% CI .07, .09), CFI of .929, and SMR of .070. The factors were rotated using a Geomin oblique rotation which allowed for correlations between the two factors. To interpret the factor structure, the rotated factors were examined for factor loadings greater than .40 (Stevens, 2002). Additionally, the standardized rotated factor loading were examined to determine if the factor loadings were significantly different from zero. As can be seen in Table 8, all of the DRAOR Stable subscale items loaded onto Factor 1. Further, the majority of the Acute subscale items loaded exclusively on this factor, so it was determined that this factor represented *Risk* items. An analysis of the loadings indicated that there were no items that had loaded on both factors. Three items (previously Acute variables 4, 5, and 6) did not surpass the threshold for a meaningful loading. An analysis of the factor structure loadings revealed that these three items still moderately to highly correlated with Factor 1 (A4: .38, A5: .37, A6: .48). These results, coupled with the marginal rotated factor loadings,

suggested that the items should be subsumed under Factor 1, however the inclusion of these items was further considered alongside the factor's internal consistency.

All of the DRAOR's protective subscale items loaded on Factor 2, which was subsequently labelled *Protective Factor.* As anticipated, the *Protective Factor* and *Risk Factor* correlated to a high degree (r = -.54).

Table 8

Factor Loadings for Two-factor Solution

Item	Description	Rotated Factor Loading (Standardized rotated factor loading)	
		Factor 1: Risk	Factor 2: Protective
S1	Peer associations	**.475 (7.056)**	-.148 (-2.119)
S2	Attitudes towards authority	**.876 (24.010)**	.054 (1.002)
S3	Impulse control	**.773 (17.075)**	-.062 (-1.169)
S4	Problem-solving	**.782 (21.300)**	.003 (0.081)
S5	Sense of entitlement	**.783 (23.731)**	-.001 (-0.031)
S6	Attachment with others	**.647 (12.143)**	-.160 (-2.706)
A1	Substance use	**.544 (8.812)**	.103 (1.476)
A2	Anger/hostility	**.487 (8.963)**	-.168 (-2.872)
A3	Opportunity/access to victims	**.675 (12.286)**	.014 (0.201)
A4	Negative mood	**.315 (4.850)**	-.120 (-1.872)
A5	Employment	**.293 (3.923)**	-.141 (-1.881)
A6	Interpersonal relationships	**.365 (6.473)**	-.212 (-3.673)
A7	Living situation	**.451 (6.988)**	-.138 (-1.932)
P1	Responsive to advice	-.231 (-3.635)	**.658 (14.380)**
P2	Prosocial identity	-.017 (-0.303)	**.789 (20.230)**
P3	High expectations	-.001 (-0.075)	**.826 (33.360)**
P4	Cost/benefits	-.119 (-2.227)	**.776 (19.746)**
P5	Social support	.046 (0.818)	**.778 (17.473)**
P6	Social control	.033 (0.569)	**.835 (20.791)**

Note: for the standardized score, the critical z score was 2.9913 (α = .0013889) based on a Bonferroni correction (.05/36). Bolded values indicate significant factor loadings.

Reliability of the DRAOR. The psychometrics of both the original DRAOR model (3 factors) and the empirically derived two-factor model were investigated. The internal consistency of the factors that comprise the model is displayed in Table 9 for the original DRAOR scale and presented in Table 10 for the empirically derived two factor model.

Table 9

Internal Consistency and Descriptive Statistics for the Original DRAOR Subscales

DRAOR Subscale	α	*M*	*SD*	# of items
Stable	.81	5.51	2.70	6
Acute	.62	6.44	2.78	7
Protective	.86	6.16	2.64	6

Table 10

Internal Consistency and Descriptive Statistics for the Two Factor Model of the DRAOR

DRAOR Factor	α	*M*	*SD*	# of items
Risk	.83	11.95	5.09	13
Protective	.86	6.16	2.64	6

Results indicated that for the most part, the factors demonstrate acceptable levels of internal consistency, except for the original DRAOR acute scale which has poor internal consistency. Amalgamating the original *Stable* and *Acute* subscales into the *Risk* scale led to improvements in internal consistency, and ultimately a more concise model than the original DRAOR model. Item-total correlations and Cronbach's alpha if items are deleted are displayed in Appendix B for the original DRAOR model, and Appendix C for the two factor model. Within the original model, results indicated that there would be no improvements to internal consistency if any of the items were removed. Item-total correlations suggested that all items were moderately to strongly related to their respective subscale total, except for some acute scale items: A1 (substance use, $r = .28$), A2 (anger, $r = .31$), A4 (negative mood, $r = .31$), and A5 (employment, $r = .30$) which demonstrated weak to moderate relationships with the total score. Generally, it is ideal to have all item-total correlations surpass .30 (Field, 2005); given their proximity to this threshold no items were removed from the scale. When the subscales were collapsed to form the Risk factor, the employment item demonstrated the lowest item-total

correlation (r = .32) indicating that all items demonstrated at least a moderate relationship with *Risk*. As a result of the mildly discrepant findings based on the factor analysis, the predictive accuracy of both models will be examined in the subsequent section.

Differentiation of recidivists and non-recidivists

Hypothesis 2: It is hypothesized that those who reoffend will demonstrate increased scores on the Stable, Acute and total DRAOR scores as compared to those who remained crime free, who are expected to score low on the risk scales and higher on the Protective scale.

The base rates for each offender outcome are presented in Table 11. Offenders who demonstrated a recidivistic event were compared to those who did not across the subscales for each model of the DRAOR. Comparisons were first performed using any recidivism (i.e. new arrest, technical violations) as the outcome variable, and then further refined to reflect only technical violations and a separate analysis examining new arrest as the outcome variable. Rearrest data were unable to be decomposed as anticipated (i.e. into general and violent reoffence) due to the low occurrence of violent reoffending. As a result all analyses involving reoffence as the outcome variable represent any rearrest, irrespective of severity. The two groups of offenders (recidivists vs. non-recidivists) were compared using independent samples t-tests. A Bonferonni correction was applied to each t-test to ensure that the family-wise error rate remained at $\alpha = .05$.

Of the 391 offenders included in the study, 187 offenders met the criteria for at least some type of recidivism. Table 12 displays the comparisons for these offenders across the DRAOR subscales as well as the Iowa Risk Assessment. Those who recidivated scored significantly higher on the DRAOR Stable, Acute, and Total scales, as well as the Risk factor from Model 2. Offenders who did not record a technical violation or new offence (i.e. non-

recidivist) scored lower on the Iowa Risk Assessment and had higher scores on the Protective scale, however these differences were not significant.

Table 11

Base Rates of Occurrence for Offender Outcomes

Offender outcome	*n*	Base Rate (%)
Technical violations	186	47.6
General reoffence	32	8.2
Violent reoffence	11	2.8
Any recidivism	187	47.8

Note: Base rates are determined according to the total sample (n = 391). Any recidivism is defined as either a technical violation or a reoffence.

Table 12

Comparisons Between Recidivists and Non-recidivists for Any Recidivism

Variable	Recidivist *M* (*SD*)	Non-recidivist *M* (*SD*)	*t*	*df*	Cohen's *d*
Iowa Risk Assessment	14.31 (4.51)	13.38 (4.98)	-1.57	252	-.20
Original DRAOR					
Stable	6.04 (2.82)	5.02 (2.49)	-3.77*	389	-.38
Acute	6.87 (2.86)	6.05 (2.64)	-2.94*	389	-.30
Protective	5.89 (2.82)	6.40 (2.45)	1.90	389	.19
Total	7.01 (7.32)	4.73 (6.21)	-3.32*	389	-.34
DRAOR Factors					
Risk	12.90 (5.31)	11.07 (4.71)	-3.61*	389	-.36

Note: Bonferonni correction $p < .05/6 = .008$. * denotes significance after correction. A subset of offenders (n = 254) had a static risk score. Any recidivism is defined as either a technical violation or a reoffence.

The same patterns emerged when examining differences between offenders who have committed a technical violation. As presented in Table 13, offenders who did not record a technical violation scored significantly lower across the Stable, Acute, Total, and *Risk* factor.

Comparisons involving the Iowa Risk Assessment and the Protective scale yielded differences in the expected direction, although not significant.

A different pattern emerged when considering only reoffence as the outcome of interest. As can be seen in Table 14, those who reoffended (*n* = 43) did not significantly differ from those who remained crime free (*n* = 348) across the DRAOR domains, static risk, or the Risk factor from Model 2. The base rate for reoffence (11.00%), and corresponding asymmetric distribution, might explain why the significant differences deteriorated when analyzing reoffending. Of note, the slight differences that were present were in the expected direction with the exception of the Stable subscale.

Table 13

Comparisons Between Recidivists and Non-recidivists For Any Technical Violation

Variable	Recidivist *M* (*SD*)	Non-recidivist *M* (*SD*)	*t*	*df*	Cohen's *d*
Iowa Risk Assessment	14.21 (4.47)	13.48 (5.02)	-1.21	252	-.15
Original DRAOR					
Stable	6.02 (2.83)	5.02 (2.52)	-3.70*	390	-.37
Acute	6.86 (2.87)	6.04 (2.64)	-2.93*	390	-.30
Protective	5.94 (2.80)	6.38 (2.51)	1.67	390	.17
Total	6.95 (7.32)	4.74 (6.31)	-2.20*	390	-.22
DRAOR Factors					
Risk	12.88 (5.33)	11.07 (4.74)	-3.57*	390	-.36

Note: Bonferonni correction $p < .05/6 = .008$. * denotes significance after correction. A subset of offenders (*n* = 254) had a static risk score.

Table 14

Comparisons Between Reoffenders and Non-reoffenders

Variable	Recidivist *M* (*SD*)	Non-recidivist *M* (*SD*)	*t*	*df*	Cohen's *d*
Iowa Risk Assessment	14.91 (5.76)	13.72 (4.67)	-1.12	252	-.14
Original DRAOR					
Stable	5.39 (2.94)	5.53 (2.67)	0.33	389	.03
Acute	6.70 (3.23)	6.41 (2.72)	-0.67	389	-.06
Protective	5.89 (3.09)	6.19 (2.59)	0.72	389	.07
Total	6.20 (8.05)	5.78 (6.70)	-0.39	389	-.03
DRAOR Factors					
Risk	12.09 (5.74)	11.94 (5.01)	-0.19	389	-.01

Note: Bonferonni correction $p < .05/6 = .008$. * denotes significance after correction. A subset of offenders ($n = 254$) had a static risk score.

Overall, Hypothesis 2 was partially supported, in that significant differences emerged between recidivists and non-recidivists when examining technical violations and any recidivism as outcome variables. However, the lack of a significant difference among the Protective scale for these outcome variables was not expected and is not consistent with previous research (Hanby, 2013; Smeth 2013). Results from comparisons of reoffence data yielded no support for Hypothesis 2, although issues with base rates may account for the lack of significant findings.

Predictive Accuracy of the DRAOR

Hypothesis 3: It is anticipated that the DRAOR risk scales and total score will successfully predict recidivism. Similarly, increased protective factors will predict successful (i.e. crime-free) community supervision.

A series of *AUC* analyses were performed to assess the predictive accuracy of the original DRAOR total score and subscales as well as the Model 2 Risk factor. Time at risk was incorporated for by extracting X*Beta standardized scores from the Cox regression survival analysis models which represent the best possible linear combination of the variables included in the model. At the univariate level, this score represents an individual's predicted survival

function. An *AUC* that corresponds to each variable at the univariate level is provided in Table 15. Further, Cohen's *d* was computed for each *AUC* value to permit additional comparisons with previous research. Results suggested that none of the variables at the univariate level significantly predicted general or violent reoffending.

Table 15

DRAOR Subscales and Total Predicting Reoffence (n = 43)

DRAOR Measure	*AUC*	SE	95% C.I.	*d*
Model 1				
Stable	.52	.05	.42, .62	.08
Acute	.53	.05	.43, .63	.11
Protective	.56	.05	.47, .66	.22
Total	.53	.05	.43, .63	.09
Model 2				
Risk	.51	.05	.41, .61	.03

Note: *n* = 43 offenders experienced either a violent or general reoffence.

The relationships between all DRAOR domains and technical violations were examined. Results suggested that all variables were able to significantly predict technical violations with varying degrees of precision (see Table 16). Specifically, the DRAOR Stable domain and Total score demonstrated the strongest effect, while the Protective subscale had the smallest effect.

Table 16

DRAOR Subscales and Total Predicting Technical Violations (n = 186)

DRAOR Measure	*AUC*	SE	95% C.I.	*d*
Model 1				
Stable	.61***	.03	.56, .67	.40
Acute	.59**	.03	.53, .65	.32
Protective	.57*	.03	.51, .63	.24
Total	.61***	.03	.56, .67	.41
Model 2				
Risk	.61***	.03	.56, .67	.40

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

When data including technical violations and reoffence were amalgamated (i.e. recidivism) results indicated that all of the DRAOR domains and total score were significantly predictive (see Table 17). Similarly, the DRAOR factor *Risk* demonstrated a moderate relationship with recidivism. Among the variables, the magnitude of the relationship with recidivism ranged from low to moderate with the DRAOR Total and Stable domain demonstrating the strongest relationship.

Table 17

DRAOR Domains and Total Score Predicting Any Recidivism

DRAOR Measure	*AUC*	SE	95% C.I.	*d*
Model 1				
Stable	.62**	.03	.56, .67	.41
Acute	.59*	.03	.54, .65	.33
Protective	.58*	.03	.52, .64	.28
Total	.62**	.03	.56, .68	.42
Model 2				
Risk	.62**	.03	.46, .67	.41

Note: * $p < .05$, ** $p < .01$, *** $p < .001$. Any recidivism is defined as either a technical violation or a reoffence.

Overall, the results indicated partial support for Hypothesis 3. When examining the relationship with reoffending, the DRAOR domains did not demonstrate the ability to differentiate between reoffenders and those who remained crime free. However, when the outcome variable was technical violations or any recidivism, all DRAOR domains demonstrated a significant relationship. It was expected that the DRAOR would be predictive of reoffence as well; however base rates were lower for this outcome compared to technical violations which might explain the null findings[2].

[2] Results for the predictive accuracy of the Iowa Risk Assessment are not presented. Only a subsample of offenders had a completed assessment and the results were unstable as evidenced by large confidence intervals.

Cox regression survival analyses.

Hypothesis 4: The DRAOR will be able to predict time to recidivism (i.e. technical violations, general reoffending, and any recidivism), with those demonstrating higher risk indicators (i.e. higher scores on DRAOR risk and total scores) failing on community supervision more rapidly than those with lower DRAOR scores.

A series of Cox regression survival analyses were conducted at both the univariate and multivariate level to examine the level in which the DRAOR domains are able to predict time until a given event (i.e. recidivism, technical violations). Initially, all original DRAOR domains were entered along with the DRAOR risk factor as derived from the factor analysis. These variables were examined to determine if they were significantly related to the outcome of interest; when a variable demonstrated a univariate relationship with the outcome variable, it was later entered into a multivariate model to assess the predictive accuracy of a combination of the variables, and to determine if each remains significant while incorporating the other variables.

Univariate results. The results from the five cox regression survival analyses examining any reoffence are presented in Table 18. Similar to the *AUC*s discussed previously, none of the variables significantly predicted time to reoffence, although only a small portion of the sample reoffended (11.00%; $n = 43$). Due to the low base rates for reoffence, and the lack of significant findings, reoffence data was unable to be decomposed to examine if the DRAOR was able to predict violent offences or general offences. Of note, those offenders who did not reoffend were at risk for an average of 265.42 days ($SD = 145.49$). Of these offenders, 50.0% were at risk for 271 days or less. The mean time at risk for those offenders who reoffended was 128.19 days ($SD = 73.31$) with 51.2% reoffending in 112 days or less.

Table 18

Univariate Survival Analysis Predicting Reoffence (n = 43)

							95% CI for *Exp(B)*	
	B	*SE*	*Wald*	*df*	*p*	*Exp(B)*	Lower Bound	Upper Bound
DRAOR								
Stable Risk	-.02	.06	.18	1	.674	0.98	0.88	1.09
Acute Risk	.04	.05	.47	1	.491	1.04	0.93	1.16
Protective	-.04	.06	.50	1	.479	0.96	0.86	1.08
DRAOR Total	.01	.02	.12	1	.732	1.01	0.97	1.05
DRAOR Factor								
RISK	.00	.03	.02	1	.879	1.00	0.95	1.06
Iowa Risk	.06	.05	1.46	1	.226	1.06	0.96	1.17

Note: only *n* = 21 offenders who had a static score (i.e. Iowa Risk) also experienced a reoffence.

In contrast, when examining the prediction of time to a technical violation, most of the DRAOR domains demonstrated a significant association (See Table 19). Specifically, the DRAOR Stable domain (-2 log likelihood = 2000.92, χ^2 (1) = 23.70, p < 001), Acute (-2 log likelihood = 2008.14, χ^2 (1) = 16.48, p < .001), DRAOR Total score (-2 log likelihood = 2006.98, χ^2 (1) = 17.64, p < .001), and DRAOR factor Risk (-2 log likelihood = 2001.82, χ^2 (1) = 22.79, p < .001) demonstrated an independent relationship with technical violations. The Protective domain narrowly did not significantly predict time to violations (-2 log likelihood = 2020.86, χ^2 (1) = 3.72, p = .054). The positive regression coefficients across the DRAOR risk domains suggested that those offenders with higher scores failed at a faster rate than those with lower scores. Although representing a trend (p = .054) results from the univariate examination of the Protective domain suggested that those offenders who scored higher successfully remained in the community (i.e. did not commit a technical violation) longer than those who scored lower across

the Protective domain. Results indicated that the Stable domain was responsible for the largest increase in the likelihood of a technical violation per one-point increase (approximately 15%). A one-point increase across the DRAOR Acute, Total, and the Risk factor led to an 11%, 5%, and 7% increase in the likelihood of a technical violation, respectively. Descriptively, offenders who did not commit a technical violation were under supervision (i.e. at risk) for an average of 246.36 days (*SD* = 142.53) with 50% of offenders at risk for 240 days or fewer. Conversely offenders who committed a technical violation were at risk for an average of 112.97 days (*SD* = 82.10) prior to breaching a condition, with 51.3% of offenders doing so in 83 days or less.

Lastly, technical violation and reoffence data was amalgamated to determine whether the DRAOR was predictive of any recidivism. Results presented in Table 20 demonstrate that the DRAOR Stable (-2 log likelihood = 2011.70, χ^2 (1) = 23.37, $p < .001$), Acute (-2 log likelihood = 2018.58, χ^2 (1) = $p < .001$) Protective (-2 log likelihood = 2030.24, χ^2 (1) = 4.74, $p = .03$), and Total score (-2 log likelihood = 2016.60, χ^2 (1) = 18.27, $p < .001$) all significantly predicted time to recidivism.

Table 19

Univariate Survival Analysis Predicting Technical Violations (n = 186)

							95% CI for *Exp(B)*	
	B	*SE*	*Wald*	*df*	*p*	*Exp(B)*	Lower Bound	Upper Bound
DRAOR								
Stable Risk	.14	.03	23.60	1	.000	1.15	1.09	1.21
Acute Risk	.11	.03	16.47	1	.000	1.11	1.06	1.17
Protective	-.06	.03	3.73	1	.054	0.95	0.89	1.00
DRAOR Total	.05	.01	17.60	1	.000	1.05	1.03	1.07
DRAOR Factor								
RISK	.07	.02	22.78	1	.000	1.07	1.04	1.10
Iowa Risk	.05	.02	7.05	1	.008	1.05	1.01	1.10

Note. 137 offenders did not have a static risk score (i.e. Iowa Risk) and *n* = 119 experienced a technical violation.

Further, the derived DRAOR factor *Risk*, significantly predicted time to recidivism (-2 log likelihood = 2012.42, χ^2 (1) = 22.56, $p < .001$). Similar to the results for technical violations, the Stable domain demonstrated the largest effect, with a 15% increase in risk for every one-point increase in score. The Protective domain indicated that every one-point increase in score (i.e. demonstrating more protective factors) led to a 6% reduction in risk to either conduct a technical violation or reoffence.

Table 20

Univariate Survival Analysis Predicting Any Recidivism (n = 187)

							95% CI for *Exp(B)*	
	B	*SE*	*Wald*	*df*	*p*	*Exp(B)*	Lower Bound	Upper Bound
DRAOR								
Stable Risk	.14	.03	23.24	1	.000	1.15	1.08	1.21
Acute Risk	.11	.03	16.43	1	.000	1.11	1.06	1.17
Protective	-.06	.03	4.75	1	.029	0.94	0.89	0.99
DRAOR Total	.05	.01	18.41	1	.000	1.05	1.03	1.07
DRAOR Factor								
RISK	.07	.02	22.59	1	.000	1.07	1.04	1.10
Iowa Risk	.06	.02	8.3	1	.004	1.06	1.02	1.10

Note: 137 offenders were missing data on the Iowa Risk Assessment. Any recidivism is defined as either a technical violation or reoffence.

Multivariate results. All variables that were found to be individually related to survival time were retained for subsequent analyses. Two models were constructed to evaluate whether the original version of the DRAOR (i.e. Stable, Acute, Protective, Total) predicted outcome stronger than Model 2 which considers the factor structure derived previously (i.e. Risk, Protective, Total). Based on the null effects for predicting reoffence, only technical violations and recidivism were used as outcome variables at the multivariate level. All reported results are based on the final step of the analyses when multiple variables were being examined. For all analyses the final step (i.e. when all variables were entered) was unable to be calculated as the covariates demonstrated redundancy and singularity was reached. An examination of Squared Multiple Correlations (SMC) suggested that the variables were highly inter-correlated with the DRAOR total score which prohibited inclusion in an overall model. As a result, only those

models where multicollinearity was not a problem are presented and discussed (the DRAOR Total score appeared to be the problematic covariate and was not included in the multivariate models).

As displayed in Table 21, when DRAOR domains were simultaneously examined, results indicated that the DRAOR Stable significantly predicted time to technical violation, whereas the Acute and Protective subscales no longer significantly predicted time to technical violations. When the DRAOR Stable and Acute domains were included simultaneously, the overall model was significant (-2 log likelihood = 2001. 22, χ^2 (2) = 25.00, $p < .001$) although only the Stable remained a significant predictor. Additionally, the results indicated that a one-point increase in the Stable domain resulted in a 12% increase in the likelihood of experiencing a technical violation. Similar results were obtained when the Stable and Protective domains were investigated concurrently, in that the overall model remained significant (-2 log likelihood = 2000.92, χ^2 (2) = 25.48, $p < .001$) although only the Stable domain retained the ability to significantly predict time to a technical violation. The previous two models demonstrated equivalent predictive accuracy when the overall model *AUC* was examined (*AUC* = .635, *SE* = .03, 95% CI .57, .70).

When all DRAOR domains (i.e. Stable, Acute, and Protective) were entered in the same block, the Stable domain continued to demonstrate a significant relationship with technical violations (-2 log likelihood = 2000.22, χ^2 (3) = 26.14, $p < .001$), although neither the Protective nor Acute domains remained significant. Compared to the previous models when only two of the domains were entered at a given time, the predictive accuracy of the overall model was lessened (*AUC* = .599, *SE* = .03, 95% CI .54, .66).

The DRAOR factor *Risk* was examined to determine if the empirically derived structure of the DRAOR enhanced the predicted time to technical violations. Results were comparable to the original DRAOR structure (-2 log likelihood = 2001.89, χ^2 (2) = 24.45, $p < .001$), such that the *Risk* factor (*Exp (B)* = 1.08, $p < .001$) was the only variable that significantly predicted time until technical violations when considered alongside the *Protective* factor (*Exp (B)* = 1.03, p = .39). However, this combination of variables yielded a lower overall level of predictive accuracy compared to the models utilizing the original DRAOR domains (*AUC* = .589, *SE* = .03, 95% CI .53, .65).

Table 21

Multivariate Analysis of the Original DRAOR Predicting Technical Violations

	Model 1			Model 2			Model 3		
		95% CI for *Exp(B)*			95% CI for *Exp(B)*			95% CI for *Exp(B)*	
Variables	*Exp(B)*	Lower Bound	Upper Bound	*Exp(B)*	Lower Bound	Upper Bound	*Exp(B)*	Lower Bound	Upper Bound
Block 1									
Stable	1.12**	1.04	1.22	1.17***	1.09	1.25	1.14**	1.05	1.24
Block 2									
Acute	1.03	0.95	1.11	-	-	-	1.03	0.96	1.12
Protective	-	-	-	1.03	0.97	1.11	1.04	0.97	1.11

Note: * $p < .05$, ** $p < .01$, *** $p < .001$

Table 22

Multivariate Analysis of the Original DRAOR Predicting Any Recidivism

	Model 1			Model 2			Model 3		
		95% CI for *Exp(B)*			95% CI for *Exp(B)*			95% CI for *Exp(B)*	
Variables	*Exp(B)*	Lower Bound	Upper Bound	*Exp(B)*	Lower Bound	Upper Bound	*Exp(B)*	Lower Bound	Upper Bound
Block 1									
Stable	1.12**	1.03	1.22	1.16***	1.08	1.24	1.13**	1.04	1.23
Block 2									
Acute	1.03	0.95	1.11	-	-	-	1.03	0.96	1.12
Protective	-	-	-	1.02	0.95	1.09	1.02	0.95	1.10

Note: * $p < .05$, ** $p < .01$, *** $p < .001$. Any recidivism is defined as either a technical violation or reoffence.

Similar to the prediction of technical violations, when the DRAOR domains were investigated simultaneously, the Stable consistently predicted time to any recidivism. As presented in Table 23, the overall model consisting of all three DRAOR domains was significant (-2 log likelihood = 2011.56, χ^2 (3) = 25.16, $p < .001$) with the Stable domain remaining significant. The results indicated that a one-point increase on the Stable domain led to an increase of approximately 13% in the likelihood of demonstrating any recidivistic event. An examination of the *AUC*s extracted from the model suggested that the combination of Stable and Acute scores led to the strongest prediction model (*AUC* = .62, *SE* = .03, 95% CI .56, .68), albeit just narrowly improving over the Stable/Protective model (*AUC* = .61, *SE* = .03, 95% CI .56, .67) and the model consisting of all three domains (*AUC* = .62, *SE* = .03, 95% CI .56, .67). As anticipated, the examination of the DRAOR factor *Risk* revealed the same pattern; the inclusion of *Risk* and *Protective* resulted in a significant model (-2 log likelihood = 2013.00, χ^2 (2) = 23.69), $p < .001$). As previously found, the *Risk* factor remained a significant predictor of any recidivism (*Exp(B)* = 1.08, *p* .001) whereas the *Protective* factor did not remain significant (*Exp(B)* = 1.02, *p* = .62). The model demonstrated equivalent predictive accuracy as compared to the previous models (*AUC* = .61, *SE* = .03, 95% CI .56, .67).

Overall, the univariate results provide partial support for Hypothesis 4, in that the DRAOR domains significantly predicted technical violations and any recidivism, but failed to predict time to reoffence. The null findings at the univariate level for reoffence prevented the examination of the relative contribution of each domain. However, multivariate analyses for technical violations and any recidivism indicated that the DRAOR Stable domain consistently predicted time to each outcome, while considering

Acute and Protective scores. The same pattern emerged when the DRAOR factors were examined, whereby DRAOR *Risk* predicted both outcomes while considered alongside the *Protective* factor.

Moderated cox regression.

Hypothesis 5: The predictive validity of the DRAOR will be enhanced at higher levels of static risk (i.e. Iowa Risk Assessment) compared to moderate and low levels of static risk.

A cox regression survival analysis was conducted to determine if static risk scores moderated the relationship between DRAOR total scores and any recidivism. Specifically, it was anticipated that scores across the DRAOR would be more salient predictors for high risk offenders (as identified by the Iowa Risk Assessment). As with previous analyses utilizing the Iowa Risk Assessment, only a subset of offenders had a valid score, restricting the current analysis to 253 offenders. As detailed in Table 23, as main effects, both measures of dynamic risk and static risk significantly predicted recidivism (-2 log likelihood = 1167.15, χ^2 (2) = 22.23, $p < .001$). When the interaction term was entered into the second block, the overall model remained significant (-2 log likelihood = 1165.67, χ^2 (3) = 25.88, $p < .001$) however no single variable demonstrated significance. Further, the non-significant change from the first block indicated that the interaction was not significant and did not meaningfully add to the prediction of recidivism (χ^2 (1) = 1.48, $p = .224$), thus Hypothesis 5 was not supported. The potential dynamic by static interaction was also examined using technical violations and reoffence as outcomes, results are not presented here for the sake of brevity, however both analyses indicated that there were no significant interactions present.

Table 23

Moderated Cox Regression Examining Static Risk x Dynamic Risk for the Prediction of Any Recidivism

	B	*SE*	*Wald*	*df*	*p*	*Exp(B)*	95% CI for *Exp(B)* Lower Bound	Upper Bound
Model 1								
Static risk	.05	.02	5.24	1	.022	1.05	1.01	1.09
DRAOR Total	.06	.02	14.17	1	.000	1.06	1.03	1.09
Model 2								
Static risk	.02	.03	0.36	1	.550	1.02	0.96	1.08
DRAOR Total	.01	.04	0.03	1	.862	1.01	0.93	1.09
Static x DRAOR Total	.00	.00	1.52	1	.218	1.00	0.99	1.01

Note. Any recidivism is defined as either a technical violation or reoffence.

Hypothesis 6: The relationships between DRAOR risk scores (i.e. Stable and Acute) will be moderated by protective factors. Protective factors will be more relevant for those offenders who demonstrate higher scores on the DRAOR risk domains.

Similar to the analyses above, a series of cox regression survival analyses were conducted to evaluate whether the effect of protective factors was stronger at higher levels of dynamic risk. The factor *Risk* that was previously extracted from the factor analysis was entered into the regression model as it represents all of the DRAOR risk items. The DRAOR Protective scale was also entered into the first block, followed by the cross-product entered alongside the DRAOR domains in the second block.

Results suggested that when analyzing the main effects, the overall model was significantly related to any recidivism (-2 log likelihood = 2012.13, χ^2 (2) = 22.93, $p <$ .001), although only the DRAOR risk domains demonstrated a significant main effect (see Table 24). The model remained significant when the interaction term was added to the model (-2 log likelihood = 2010.19, χ^2 (3) = 27.29, $p <$ .001) however the interaction term was not significant nor was the change from the previous model (χ^2 (1) = 1.62, $p =$ .20). This suggested that the relationship between DRAOR protective factors and recidivism did not vary depending on the level of dynamic risk that the offender demonstrated; as a result, Hypothesis 6 was not supported.

In summary, investigation into a potential interaction between static risk and dynamic risk suggested that relationship between dynamic risk and recidivism did not vary depending on the level of static risk of the offender. Further, results indicated that a hypothesized interaction between risk and protective factors was not present, suggesting

that protective factors were no more meaningful for higher risk offenders than for lower risk offenders.

Table 24

Moderated Cox Regression Examining Protective Factors x Dynamic Risk for Prediction of Any Recidivism

	B	*SE*	*Wald*	*df*	*p*	*Exp(B)*	95% CI for *Exp(B)* Lower Bound	Upper Bound
Model 1								
DRAOR risk	.08	.02	18.25	1	.000	1.08	1.04	1.12
Protective	.02	.04	0.30	1	.586	1.02	0.95	1.09
Model 2								
DRAOR risk	.11	.03	13.90	1	.000	1.11	1.05	1.18
Protective	.09	.06	2.21	1	.137	1.09	0.97	1.23
DRAOR risk x Protective	-.01	.00	2.06	1	.152	1.00	0.99	1.00

Note. Any recidivism is defined as either a technical violation or reoffence.

Discussion

Summary of findings

This was the first validation study examining the DRAOR among a sample of general offenders in the U.S. As such, this study sought to validate the use of the DRAOR to encourage continued use, as well as determine whether the DRAOR performed similarly to what was found in other jurisdictions (e.g. Hanby, 2014; Yesberg et al., 2013). The construct validity of the DRAOR was examined at the first assessment, which must have occurred within 60 days, to ensure that the DRAOR was capturing an offender's risk during the time that offenders are typically experiencing elevated risk to reoffend.

The results of an Exploratory Factor Analysis generated one model that provided a slight variation in the organization of the original DRAOR items and subscales. Reliability analyses suggested that both models were sufficiently reliable and were generally successful in predicting recidivism and technical violations, however unable to predict reoffending. Although a more thorough validation may be necessary, the results obtained from the two models were not substantially different; thus utilizing the structure of the original model is recommended to allow for the differentiation between Stable and Acute dynamic risk factors. As a result, further discussion will emphasize the original structure of the DRAOR rather than presenting both models as results remained consistent through all analyses. Although all original items were retained in Model 2, future research should examine the importance of negative mood, employment, and interpersonal relationships as these items failed to meet the factor loading threshold. Nonetheless, their inclusion did not reduce the overall internal consistency of the scale.

Comparisons between groups of offenders highlighted the ability of the DRAOR to differentiate between recidivists and non-recidivists for various offender outcomes. As expected, offenders who either conducted a technical violation or demonstrated any recidivism scored higher on average across the Stable, Acute, and DRAOR Total than compared to those offenders who remained crime-free. Contrary to expectations, the Protective domain was unable to differentiate between recidivists and non-recidivists. Further, the DRAOR domains failed to produce any differences when those offenders who recorded a new arrest were compared with those who remained crime-free.

The predictive accuracy of the DRAOR was evaluated using ROC analysis. The DRAOR and its subscales consistently demonstrated the ability to predict technical violations and any recidivism. The Stable domain and Total score produced the largest effect (*AUC*s of .61-.62), albeit still classified as small according to Rice and Harris' (2005) recommendations. Contrary to expectations, the DRAOR was unable to predict whether an offender was likely to reoffend. The small magnitude of the *AUC*s and the inability to predict reoffence is inconsistent with previous research (e.g. Hanby, 2013, Yesberg et al., 2013). Past research found support for the prediction of reconviction, with *AUC*s ranging from .66 to .72 (Hanby, 2013). Additionally, multiple studies previously obtained *AUC*s for the prediction of violations substantially larger than the current study (Hanby, 2013; Smeth, 2014; Yesberg et al., 2013). These results are predominantly based on data from New Zealand, so it is possible that the differing composition of the offender population in Iowa has impacted the results. However, an initial pilot evaluation of the DRAOR in Iowa (n = 500 offenders; Serin, Prell, & Hanby, 2014), suggested that DRAOR total scores were predictive of serious violations (*AUC* = .67), new crimes (*AUC*

= .64), and any violation (*AUC* = .67) at the first assessment which suggests that the DRAOR has performed reasonably well among a sample of offenders in Iowa. The current results incorporated the time at risk within the calculation of the *AUC*; although comparisons with standard *AUC*s (i.e. not considering time at risk) produced no overly discrepant findings.

Results from the various cox regression survival analyses suggested that the Stable domain significantly predicted time to technical violations. The findings suggested that every one-point increase in the overall Stable domain led to an approximate increase of 15% in risk to conduct a technical violation. When predicting technical violations at the univariate level, all DRAOR domains demonstrated a relationship with offender outcome. However, when DRAOR domains were considered simultaneously, adding information regarding Acute and Protective did not significantly add to the prediction of any outcome. The predictive accuracy of the overall model was enhanced to a moderate effect when Stable, Acute, and Protective scores were simultaneously considered. Although Stable scores demonstrated the largest overall effect size, these results suggest that it is important to consider information across the DRAOR domains. Given that the first assessment was utilized for all analyses, it is intriguing that the domain that is expected to fluctuate the least represented the strongest predictor. If the most proximal assessment was utilized, results may have demonstrated that Stable scores become less relevant, and Acute scores greatly enhance prediction.

The results of the moderation analyses suggested that the relationship between dynamic risk and offender outcome did not differ depending on the offender's static risk score. As main effects both static and dynamic risk predicted recidivism, but it did not

appear that dynamic risk is more salient for those offenders who demonstrate high levels of static risk. This research question was exploratory in nature, and although the results are based on a small sample, initial findings suggest that considering dynamic risk is important for any offender, irrespective of static risk.

Similarly, the results of the moderation analysis examining the impact of protective factors on the relationship between dynamic risk and recidivism revealed no significant findings. As a main effect, Protective factors were not significantly related to the prediction of any recidivism. Further, the non-significant interaction term suggested that protective factors did not ameliorate the risk for future recidivism. The absence of a significant interaction term is consistent with previous research that has examined the interaction between risk and protective factors. Among adult offenders, Ullrich & Coid (2011) found that interactions between risk and protective factors were not significant, although protective factors did demonstrate an independent main effect with offender outcome. Similar findings were obtained in a sample of sex offenders under community supervision in Iowa, whereby the Protective factors (measured by the DRAOR) demonstrated an independent main effect with technical violations but the interaction was not significant (Smeth, 2014).

Implications

Given that this was the first validation study of the DRAOR among a sample of general offenders in the United States, it was important to investigate the appropriateness of the factor structure. The results suggested that there was substantial consistency between the original model, and the empirically derived model, indicating that all items originally included should remain. Although the Stable and Acute factors were

amalgamated into one factor, the protective factors demonstrated that they are independent of risk, consistent with the original conceptualization within the DRAOR. Coupled with the indices of reliability and validity, the results suggested that the original model of the DRAOR is appropriate for use with this sample of offenders. However, a more representative sample of general offenders is required to ascertain the suitability of utilizing the DRAOR for all general offenders in Iowa.

Uncovering the hypothesized complex relationships between dynamic risk, protective factors, and recidivism requires multiple steps. The results of this study contribute to satisfying the first step. The initial results support the utility of the DRAOR and indicate that at a single time point, variables that are hypothesized to be changeable are important considerations when predicting whether an offender will commit a technical violation. The ability to establish that an offender may be at risk to commit a technical violation during their supervision ensures that supervision officers are aware of their client's risk and can potentially refine case planning to mitigate potentially problematic scenarios. The utilization of the first assessment (i.e. an assessment that occurred within 60 days) also proves valuable as supervising officers can obtain information regarding their client early on in the supervision process, and use this to inform case planning and risk management. The use of the DRAOR has the potential to simplify the initial steps of case management by highlighting the risk factors that are problematic for an offender. Case managers can utilize this information to immediately make decisions regarding frequency of contact, particular conditions to be imposed, and specific recommendations for intervention strategies.

Although the results suggested that protective factors failed to significantly predict recidivism or technical violations above and beyond the Stable domain, protective factors did appear to be relevant considerations at the univariate level. Albeit a small relationship, offenders who demonstrated higher scores on protective factors were more likely to successfully remain on community supervision (i.e. did not commit a technical violation) than did offenders who had fewer protective factors. Thus far, the extant literature surrounding the role of protective factors is inconclusive, although assessing their presence is thought to have two primary implications. First, examining protective factors for an offender demonstrates that the supervising officer is aware of their prosocial behaviours/thoughts and is considering them when rendering an overall assessment of risk. This is anticipated to encourage offenders to make prosocial gains as they can recognize that their positive behaviour will make an impact on their progression through community supervision. Second, rather than solely focussing on the negative aspects of an offender's circumstance (i.e. risk factors and problems they present), emphasizing client's strengths may contribute to an enhanced working relationship with their officer. Previous research has indicated that an officer-client relationship that is characterized as warm, caring, and trusting can lead to reductions in overall recidivism rates (Dowden & Andrews, 2004; Kennealy, Skeem, Eno Louden, & Manchak, 2012). Assessing and discussing protective factors with offenders may be an initial step towards establishing this relationship.

Additionally, protective factors may represent some of the internal and external transitions that influence a shift towards desistance from crime (Serin & Lloyd, 2009). By promoting the acquisition and maintenance of protective factors among offenders, and by

incorporating them into the overall assessment of risk, officers may be contributing to the initiation of crime cessation. Identifying which factors may promote desistance could facilitate an evidenced-based allocation of resources to ensure that those offenders who are lacking specific factors are provided with the required support. Although the current study provided only limited support for the inclusion of protective factors, they appear to remain important considerations nonetheless. An examination of the impact of protective factors among a representative sample of offenders in the U.S. will likely provide a more accurate portrayal of the relative importance of protective factors.

Limitations and future research

There were various methodological limitations that likely undermined the results of this study. This study represented the initial stages of the implementation of the DRAOR in Iowa which created challenges that could have impacted the results. The current study was limited in that parole officer characteristics, including training attendance, was unable to be considered. The importance of training integrity and familiarity with an assessment tool has previously been highlighted (Flores, Lowenkamp, Holsinger, & Latessa, 2006). An examination of the fluctuations in predictive accuracy based on training conditions suggested that when a risk assessment was administered by an untrained supervision officer, the predictive accuracy of the tool diminished substantially (Flores et al., 2006).

For the current project, initial training efforts were directed at a subset of officers and managers who then trained remaining officers within their office. A total of 165 offenders were supervised by officers who received the training as described in the procedure, whereas the remaining 226 offenders were supervised by officers who

received some unspecified variation of the training from the originally formally trained officers and managers. As a result, we were unable to ensure that every officer was receiving the same instructions regarding the DRAOR, or if they were comfortable with scoring each item. An examination of the predictive accuracy based on the training status of the officers was conducted and results were consistent with Flores and colleagues (2006). The most drastic difference in predictive accuracy was for the prediction of any recidivism where DRAOR scores for trained officers demonstrated a moderate relationship with recidivism (*AUC*s ranging from .62-.69) whereas DRAOR assessments scored by informally trained officers yielded no significant relationship with recidivism (*AUC*s ranging from .52-.58). A full comparison of the predictive accuracy among these two groups of officers is presented in Appendix D. Overall, across the various offender outcomes considered in this study, the DRAOR domains scored by formally trained officers consistently demonstrated stronger predictive ability as compared to the assessments scored by the informally trained officers.

Additionally, the DRAOR remains a new assessment tool that many officers would be unfamiliar with, which likely contributed to the diminished predictive accuracy observed in this study. The level of confidence scoring the DRAOR was unable to be considered, particularly the nature of the data prevented the ability to ensure that officers were scoring the DRAOR items correctly. As previously mentioned, some assessments also included a description justifying the scoring for that item, and in a small portion (5%) of instances these descriptions reflected the opposite of the scoring (i.e., scorer error). Potentially, officers made additional scoring issues which were unable to be captured, which may have impacted the results. Further, previous research indicated that

when an assessment tool was implemented for fewer than 3 years the relationship with total scores and recidivism was substantially lower than when an assessment tool has been implemented for longer than 3 years (Flores et al., 2006). Consistent with previous research, the results suggest that is it critical to ensure that officers receive formal, structured training on the use of the DRAOR. By doing so, it is anticipated that the predictive ability of the DRAOR will be enhanced, as will the decisions that follow the results of the assessment. At the very least, future research should aim to incorporate these two variables (i.e. training and years using the tool) into analyses to examine the impact on predictive utility.

Similarly, inter-rater reliability has yet to be examined on the DRAOR to evaluate the extent that different officers reach the same conclusions regarding an offender's risk areas. Future research that examines inter-rater reliability would contribute to validating the DRAOR and enhancing training, if required. Lastly, as the scale continues to be validated it is important to examine whether the DRAOR performs similarly across various demographic variables (e.g. gender, ethnicity). This information will be critical for correctional decision makers when evaluating whether the DRAOR will be appropriate for use with their offender sample.

Explicitly emphasizing various guidelines that will strengthen the overall evaluation of the DRAOR is also critical. The current study was the first to implement the restrictive criterion of requiring that the assessment must be completed within 60 days. Although this likely contributed to a more accurate representation of overall risk during the initial stages of supervision, the eligible sample of offenders was substantially reduced and generalizability of the results was impacted. If future studies apply this

decision rule, it is imperative that officers are encouraged to complete assessments within 60 days. Building in an automated system to provide reminders to officers would be ideal. By doing so, this would also ensure that officers are beginning the case planning process as early as possible and using the results from the DRAOR to inform supervision objectives and interventions.

Although the initial assessment is critical for the development of the supervision plan and objectives, it has been suggested that the most proximal assessment to the recidivistic event proves to be the most predictive (Hanby, 2014, Hanson, 2006). The current study was limited in that it only examined the first assessment, and was unable to examine any change among the DRAOR domains, nor was is able to examine if the predictive accuracy of the DRAOR improved over time. Future studies that examine the predictive ability of the DRAOR utilizing the assessment most proximal to the outcome event are anticipated to yield stronger *AUC*s than what was obtained in this study. Further, examining change among DRAOR domains is anticipated to lead to more relevant case-based decisions. For example, if an officer conducts an assessment and determines that an offender suddenly has a problem with substance abuse, they can immediately make recommendations for substance abuse treatment to attempt to mitigate the risk. Examining the importance of within-offender change among general offenders in Iowa can potentially establish benchmarks for officers to encourage among the offenders they supervise. For instance, if results suggest that when an offender demonstrates a reduction of 5 points on the DRAOR their overall risk to reoffend reduces substantially, offenders will have clear guidelines and objectives to reduce their risk to reoffend. Future research should investigate whether these benchmarks can be established, and whether

such benchmarks can directly lead to modifications to the supervision order. In doing so, the efficiency of community corrections could be greatly increased as officers might receive automatic recommendations to modify the frequency of contact based on the most recent DRAOR assessment.

The limited sample size of the current study likely impacted the results of the moderation analyses. Although sufficient, the sample size reduced the power to detect significant effects; future research should examine whether the relationship between dynamic risk and recidivism varies depending on the level of static risk. In order to improve case planning procedures, it is important to understand if the impact of DRAOR scores differs according to static risk. Potentially, DRAOR scores are more salient for higher static risk offenders, such that they may be more likely to reoffend compared to a low static risk offender who scored similarly on the DRAOR, given the predictive accuracy of static risk scales. Accordingly, community supervision officers would need to consider both static and dynamic risk scores when making case related decisions (i.e. modifying frequency of contact).

The inconsistent presence of static risk scores for offenders in this study further limited the analyses in this study. As a result, the impact of DRAOR domain scores above and beyond (i.e. incremental validity) static risk scores was unable to be considered. The existing literature examining the predictive impact of dynamic risk factors above static risk has been inconclusive (e.g. Caudy et al., 2014; Hanson et al., 2007; Morgan et al., 2013). A thorough examination of how the DRAOR domains perform when considering risk will inform whether dynamic factors are equally relevant for the prediction of recidivism and for case planning and management. Similarly,

examining whether increases in dynamic risk signal the imminence of a future crime is of substantial utility and should be examined in future research. This could directly inform a systematic procedure that flags offenders who are currently struggling, and prompting officers to act to mitigate risk immediately. Additionally, future research would benefit from examining the importance of offender change across the DRAOR domains categorized by static risk. Previous research has suggested that reductions in total risk score for high risk offenders (i.e. moving from high risk to moderate risk) leads to more dramatic reductions in recidivism than compared to reductions in risk for low risk offenders (Vose et al., 2013). Determining if a similar pattern is observed with the DRAOR will also contribute to case management practices, particularly the allocation of resources to ensure that those offenders who are making progress are continually supported, while those high risk offenders who have yet to make progress are given even more attention.

Lastly, in order to accurately capture changes in the offender's circumstances, it is recommended that the DRAOR is administered monthly. It is anticipated that the efficacy of the supervision session would be increased if officers structure their session according to the results of an earlier assessment. Using a structured system throughout one-on-one sessions with offenders has been identified as a key component to effective community supervision (Dowden & Andrews, 2004). Future research would benefit from examining whether officers' use of the DRAOR enhances the structure of the session and contributes to an increased use of community resources (e.g. treatment programs).

Conclusion

This study marked the first comprehensive validation of the DRAOR in a U.S. sample of general offenders. Although the magnitude of findings were not as strong as previous research on the DRAOR, the current study provided initial support that the DRAOR is a valid risk assessment procedure, particularly when concerned with predicting technical violations. The preliminary results provided sufficient support for the continued use of the DRAOR which will permit the examination of more sophisticated research questions and the practical utility (i.e. informing case based decisions) of the DRAOR.

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Appendix A. DRAOR Scale

Date:_____ Name:_____Age:_____PRN number: _____Time on Supervision (mths)_____

Offender reoffended/ violated conditions? **NO** ☐ **YES** ☐ **Breach** ☐ **Recall** ☐ **New offence** ☐ **Reimprisoned** ☐

STABLE RISK INDICATORS

Characteristics associated with risk and capable of changing over months or years.

INDICATOR	**SCORING CRITERIA**	**SCORE** **(omit if unknown)**		
Peer Associations	Has only prosocial peers (0) – Has only antisocial peers (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem

Attitudes Towards Authority	Prosocial attitudes (0) – Antagonistic attitudes (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
Impulse control	Autonomous/self monitoring (0) – Highly impulsive (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
Problem-Solving	Ability to make good decisions (0) – No consideration of consequences (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
Sense of Entitlement	Recognition of their limitations (0) -Inflated sense of self worth (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
Attachment with Others	Connected/concerned about others (0)- Callous/indifferent towards others (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
		Total STABLE Risk	/ 12	

ACUTE RISK INDICATORS

Characteristics associated with risk and capable of changing in the short term (<1 month).

INDICATOR	**SCORING CRITERIA**	**SCORE** **(omit if unknown)**		
Substance Abuse	Maintaining sobriety/social use (0) – Problematic substance abuse (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
Anger/Hostility	Absence of anger/hostility (0) – Marked presence of anger/hostility (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
Opportunity/Access to Victims	Avoidance of preferred victims (0) – Access to preferred victims (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem

Negative Mood	No evidence of depression/anxiety (0) – Marked presence of depression/anxiety (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
Employment	Maintaining a job (0) – Unemployed (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
Interpersonal Relationships	In a stable healthy relationship (0) – No relationship/conflicted relationship (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
Living Situation	Stable and positive living situation (0) – Instability/Lack of accommodations (2)	**0** Not a problem	**1** Slight/Possible problem	**2** Definite problem
		Total ACUTE Risk		/ 14

PROTECTIVE FACTORS

Characteristics that may buffer risk.

INDICATOR	**SCORING CRITERIA**	**SCORE (omit if unknown)**		
Responsive to Advice	Follows direction from prosocial peers, partners, supervisor, etc..	**0** Not an asset	**1** Slight/Possible asset	**2** Definite asset
Prosocial Identity	Legitimately views self as no longer criminally oriented with behavioural examples.	**0** Not an asset	**1** Slight/Possible asset	**2** Definite asset
High Expectations	Individual, family, and/or community have high expectations of success.	**0** Not an asset	**1** Slight/Possible asset	**2** Definite asset

Costs/Benefits	Evidence that rewards of prosocial behaviour outweigh those of procriminal behaviour.	**0** Not an asset	**1** Slight/Possible asset	**2** Definite asset
Social Support	Evidence that meaningful and accessible prosocial supports exist.	**0** Not an asset	**1** Slight/Possible asset	**2** Definite asset
Social Control	Conformity and compliance with prosocial others; Strong internalized connection/bonds.	**0** Not an asset	**1** Slight/Possible asset	**2** Definite asset
		Total PROTECTIVE	/ 12	

DRAOR SCORING PROTOCOL		
Total Stable Risk Score	**A**	**/12**
Total Acute Risk Score	**B**	**/14**
Total Protective Factor Score	**C**	**/12**

Using information from administration of the DRAOR decide on the:

Most likely risk scenario? _____

Most serious risk scenario? _____

Rate how concerned you are that this person will reoffend prior to seeing him again?

Not concerned **Very concerned**

1 2 3 4 5 6

As a result of this concern, do you intend to modify the frequency of supervision?

Increase **Maintain** **Decrease**

Will you seek supervision/guidance from SPO or Service Manager?

Possible referral to a suitable programme to address risk issue?

Consider contact Psychological Services for -case consultation, or referral for assessment/treatment

NOTES

Identify any other factors that may be relevant for increasing OR decreasing risk

ITEM	IMPACT on overall risk (circle)
1.	↑ ↓
2.	↑ ↓
3.	↑ ↓
4.	↑ ↓
5.	↑ ↓

LIST CURRENT OR PLANNED MANAGEMENT OF OFFENDER

Appendix B. Reliability analyses for original DRAOR scale

Table 1

Item-total Correlations for Stable Subscale

Item	Corrected item-total correlation	Cronbach's Alpha if item deleted
Peer association	.43	.81
Attitudes toward authority	.68	.75
Impulse control	.62	.77
Problem solving	.60	.77
Sense of entitlement	.57	.78
Attachment to procriminal peers	.52	.79

Note: 6-item scale Cronbach's α = .81

Table 2

Item-total Correlations for Acute Scale

Item	Corrected item-total correlation	Cronbach's Alpha if item deleted
Substance use	.28	.60
Anger	.31	.58
Access to victims	.42	.55
Negative mood	.31	.59
Employment	.30	.59
Interpersonal relationships	.34	.58
Living situation	.38	.56

Note: 7-item scale Cronbach's α = .62

Table 3

Item-total Correlations for Protective Scale

Item	Corrected item-total correlation	Cronbach's Alpha if item deleted
Responsive to advice	.62	.84
Prosocial identity	.65	.83
High expectations	.67	.83
Cost/benefits	.68	.82
Social support	.57	.84
Social control	.66	.83

Note: 6-item scale Cronbach's α = .86

Appendix C. Reliability analyses of 2 factor model of the DRAOR

Table 1

Item-total Correlations for Risk Scale

Item	Corrected item-total correlation	Cronbach's Alpha if item deleted
Peer association	.46	.82
Attitudes toward authority	.67	.81
Impulse control	.62	.81
Problem solving	.61	.81
Sense of entitlement	.57	.81
Attachment to procriminal peers	.59	.81
Substance use	.38	.83
Anger	.42	.83
Access to victims	.52	.82
Negative mood	.33	.83
Employment	.32	.84
Interpersonal relationships	.39	.83
Living situation	.45	.82

Note: 13-item scale Cronbach's α = .83

Table 2

Item-total Correlations for Protective Scale

Item	Corrected item-total correlation	Cronbach's Alpha if item deleted
Responsive to advice	.62	.84
Prosocial identity	.65	.83
High expectations	.67	.83
Cost/benefits	.68	.82
Social support	.57	.84
Social control	.66	.83

Note: 6-item scale Cronbach's α = .86

Appendix D. Comparison of predictive accuracy across officer training status

Table 1

Prediction of Technical Violations for DRAORs Scored by Informally Trained Officers

Variable	*AUC*	SE	95% CI
Stable	.583*	.04	.505, .660
Acute	.547	.04	.469, .626
Protective	.550	.04	.471, .628
Total	.570	.04	.492, .648

Note: 82 conducted a technical violation, * $p < .05$

Table 2

Prediction of Technical Violations for DRAORs Scored by Formally Trained Officers

Variable	*AUC*	SE	95% CI
Stable	.639**	.04	.554, .724
Acute	.578	.05	.491, .666
Protective	.549	.05	.460, .638
Total	.618*	.04	.532, .704

Note: 68 conducted a technical violation, *$p < .05$, **$p < .01$

Table 3

Prediction of Reoffence for DRAORs Scored by Informally Trained Officers

Variable	*AUC*	SE	95% CI
Stable	.382	.08	.238, .527
Acute	.450	.07	.295, .606
Protective	.472	.09	.300, .645
Total	.411	.08	.249, .572

Note: 19 had a reoffence

Table 4

Prediction of Reoffence for DRAORs Scored by Formally Trained Officers

Variable	*AUC*	SE	95% CI
Stable	.515	.06	.390, .640
Acute	.554	.07	.427, .681
Protective	.575	.05	.470, .679
Total	.546	.06	.429, .663

Note: 25 had a reoffence

Table 5

Prediction of Any Recidivism for DRAORs Scored by Informally Trained Officers

Variable	*AUC*	SE	95% CI
Stable	.554	.04	.477, .632
Acute	.524	.04	.447, .601
Protective	.523	.04	.445, .601
Total	.541	.04	.463, .619

Note: 97 offenders demonstrated a recidivistic event.

Table 6

Prediction of Any Recidivism for DRAORs Scored by Formally Trained Officers

Variable	*AUC*	SE	95% CI
Stable	.680***	.04	.598, .762
Acute	.647***	.04	.562, .732
Protective	.617**	.04	.531, .703
Total	.685***	.04	.603, .767

Note: 91 offenders demonstrated a recidivistic event. $^{**}p < .01$, $^{***}p < .001$