# Enhancing Criminogenic Needs Assessment with Regular Reassessments of Acute Dynamic Risk: DRAOR Adds to PCRA's Recidivism Prediction for Red Band Cases

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**TO SUPPORT INDIVIDUALS** to live crime-free in the community, United States federal probation officers rely on evidence-based

<sup>1</sup> We are responsible for the views expressed in this article and these are not necessarily shared by the Administrative Office of the United States Courts. Caleb D. Lloyd is a co-author of the 2017 version of the DRAOR scoring manual and co-developer of the DRAOR training program and training certification.

The Western District of Oklahoma, U.S. Courts, owns the data described in this article; we used these data with their permission and can share the data only with written permission from appropriate authorities responsible for these data. Analysis code for this study is available by emailing the first author.

We thank Jay Mauldin at Western District of Oklahoma for his partnership to conduct this study. This project would not have been possible without your generous efforts and collaboration throughout the implementation and evaluation process. We also thank the 27 USPOs who attended training, engaged with DRAOR, and recorded assessments, and we thank all management and leadership staff at the district office for supporting the project.

Correspondence concerning this article should be addressed to Caleb D. Lloyd, Centre of Forensic Behavioural Science, Swinburne University of Technology, Level 1, 582 Heidelberg Road, Alphington, VIC 3078, Australia. E-mail: cdlloyd@ swin.edu.au practices (i.e., assessment, management, and intervention strategies associated with reduced recidivism). Empirically validated standardized risk assessment tools are foundational to evidence-based community supervision (Bonta & Andrews, 2023). Understanding of best practices in risk assessment continues to evolve, and policies guiding implementation of these practices have changed in tandem (Administrative Office of the United States Courts [AO], 2018). Key among these changes is adoption of assessment tools that incorporate dynamic (changeable) risk factors (Johnson et al., 2011), because such tools identify targets for intervention while also predicting recidivism (Bonta & Andrews, 2023; Serin et al., 2016).

#### Developing PCRA Toward Violence Risk Management

In 2010, the Administrative Office of the U.S. Courts (AO) developed the Post Conviction Risk Assessment (PCRA) tool (Johnson et al., 2011). PCRA improved on the federal probation system's previous risk assessment tools by facilitating probation officers to detect change in risk factors theorized to be relevant for rehabilitative gains and successful completion

of supervision orders. In 2014, the AO began developing PCRA 2.0 that included a trailer of items to specifically predict violence (AO, 2018). When determining items that maximized prediction of violent recidivism, the PCRA 2.0 developers also attended to how these risk factors could guide officers' understanding of specific, individualized drivers of violence and guide targeted intervention to address these drivers (Serin et al., 2016).

For example, Serin and colleagues (2016) suggested prior family violence convictions (i.e., a static, or unchangeable, risk factor) implied the individual's violence may be goaldirected, requiring a probation officer to target instrumental antisocial thinking styles alongside ongoing monitoring of victim access. Similarly, the presence of stable dynamic risk factors (that can change, but are relatively slow-changing) such as high power orientation beliefs and gang affiliation would imply the need to target closely related antisocial cognitions (e.g., justifications and rationalizations), antisocial peers, and acute dynamic risk factors (that can change rapidly over days, hours, or minutes) such as emotional reactivity or anger (Serin et al., 2016; see also Hanson & Harris, 2000). For ongoing management,

Serin and colleagues (2016) highlighted how even relatively stable criminogenic needs (e.g., negative emotionality, or tendency toward hostility, within antisocial personality pattern) can have corresponding expression through quickly fluctuating acute risk factors (e.g., through levels of anger).

PCRA 2.0 and its violence trailer include some dynamic risk factors theorized to be stable and some acute (see Table 1). This feature aligns with the risk assessment goal to establish which criminogenic needs and acute dynamic risk factors are currently present, so officers can intervene at the existing level of risk and adjust their approach as risk for violence increases. The challenge for risk management is that some key indicators of violence risk are likely to emerge between scheduled reassessments of stable criminogenic needs. PCRA is implemented so reassessment occurs every 6 or 12 months, and PCRA does not output separate summary scores for acute dynamic risk factors. Thus, monitoring and management of acute risk relies on probation officers' individualized and proactive consideration of current challenges and how criminogenic needs may be presently manifesting in acute ways.

Since PCRA 2.0's development, there has

been an increasing volume of evidence from risk assessment studies in community corrections that support the importance of relatively frequent reassessment of acute risk factors for predicting violence (for example, see Stone et al., 2021) and sexual violence (Babchishin & Hanson, 2020). On the foundation of emerging research evidence, corrections agencies worldwide have adopted tools that assess acute dynamic risk (see e.g., Bourgon et al., 2018; Coulter & Lloyd, 2023; Lloyd et al., 2020; Rieger et al., 2024). In U.S. federal probation, a retrospective month-by-month file-review study explored if supplementing PCRA with scores representing acute dynamic risk improved prediction of violent recidivism; Lowenkamp and colleagues (2016) compared a sample selected for violent recidivism to a matched sample. Results suggested acute dynamic risk scores and particularly some risk factors (i.e., anger, negative mood, and victim access, which are all potentially fast-changing) differentiated those with violent recidivism. However, the study's pre-selected sample and retrospective methodology limited conclusively establishing predictive validity.

## Acute Dynamic Risk Factors Require Reassessment

Acute dynamic risk factors typically sit within the same domains as criminogenic needs. The key difference is a narrowed focus on shorter, up-to-date time frames and recent fluctuations (e.g., current emotional states, recent employment and/or relationship volatility). Acute factors can change rapidly (Hanson & Harris, 2000), and, ideally, reassessment matches the rate at which acute factors change to best inform risk management and intervention (Douglas & Skeem, 2005). For example, in forensic hospital settings, staff update Dynamic Appraisal of Situational Aggression (DASA) violence risk scores every 12 to 24 hours (Ogloff & Daffern, 2006). This frequency allows forensic nurses to respond quickly and use less restrictive interventions from work shift to work shift, supporting a more rehabilitative case management approach (Maguire et al., 2019).

In community corrections, many researchers have examined large datasets with frequent assessments to establish the optimal timing of acute dynamic risk reassessment for prediction (e.g. Babchishin & Hanson, 2020; Davies et al., 2022, 2023; Lloyd et al., 2020;

TABLE 1. Static, stable dynamic, and acute dynamic risk factors included in PCRA 2.0 and its violence trailer.

#### **Acute Dynamic Risk Factors Static Risk Factors Stable Dynamic Risk Factors** Number of prior arrests Work history and stability over **Employment status** Prior violent arrests the past 12 months Disruptions at work, school, and home due to drug or alcohol use Arrest for more than one type of offending Marital status New criminal behavior while under supervision Degree of prosocial support Uses drugs or alcohol when it is physically hazardous Continues to use drugs or Problematic institutional adjustment while Nature of relationship with peers imprisoned PCRA 2.0 Age at the time of supervision Antisocial cognitions alcohol despite social and Highest level of education achieved Motivation, or attitude towards interpersonal problems supervision and change Current drug or alcohol problem Relationship status with significant other Unstable family situation Current arrest for general violence, domestic Gang member or affiliation Recent breakup with significant violence, sexual crime, or failure to register with a gang Age at first criminal justice contact Power orientation beliefs Recent treatment non-Prior arrests for violence, domestic violence, **Entitlement beliefs** compliance stalking, arson, menacing, harassing, threatening, Denial of harm beliefs sexual assault, or violation of a restraining or Self-assertion/deception beliefs personal protection order Evidence past violent criminal conduct was preplanned Violence Trailer Ever used a weapon in the commission of a crime within PCRA 2.0 Victimized a stranger during past violent conduct Sexual assaults of unrelated male victims under the age of 17 History of polysubstance abuse Prescribed psychotropic medication at the time of sentencing, while incarcerated, or at the time of the assessment Ever admitted to a hospital or psychiatric institution for mental health reasons

Stone et al., 2021, 2022). Several studies using Dynamic Risk Assessment for Offender Reentry (DRAOR; Serin, 2007) scores indicated that reassessment every week to 2 weeks improved prediction of imminent recidivism of any type (Davies et al., 2022; Lloyd et al., 2020; Stone et al., 2022) and violent recidivism, specifically (Stone et al., 2021). For predicting sexual recidivism, Lee and colleagues (2024) found updating ACUTE-2007 (Hanson et al., 2007) scores every month to 6 weeks was optimal, whereas these acute dynamic assessments had "expired" past their "shelf life" by 4 to 6 months.

Thus, the advantages gained from measuring acute dynamic risk factors rest as much on the timing of reassessment as the content domains. The history of PCRA's development includes systematically trialing some non-scored items that, conceptually, are acute dynamic risk (e.g., recent employment instability, problems related to drug use, housing instability) and strength factors (e.g., prosocial family support, engagement in prosocial activities), but that, in practice, officers updated on the same time frame as stable criminogenic needs (Cohen & Bechtel, 2017). Cohen and Bechtel's (2017) analysis showed that although several of the non-scored PCRA items predicted overall and violent recidivism (and were valuable considerations for case planning), placing the non-scored items into PCRA's algorithm did not substantially enhance its prediction. Given recent findings clarifying there is an optimally shorter "shelf life" of acute dynamic assessments, PCRA's non-scored items may have meaningfully changed between reassessments, but these dynamic changes were not reflected in the relatively slower assessment schedule. If so, non-optimal timing may have undermined their potential predictive value. For example, scoring both "recent employment instability" and "employment" over the past 6-12 months may be overlapping and redundant for prediction, whereas scoring "current employment problems" each month as a fully dynamic risk item may better assess the true instability of employment and better reflect the current likelihood of recidivism. The "real time" instability in a risk domain may provide an additionally useful vantage point, even after accounting for that risk domain over a longer time frame.

### **The Present Study**

In this study, we partnered with U.S. federal probation's Western District of Oklahoma to

implement a risk tool with acute dynamic risk factors (i.e., Dynamic Risk Assessment for Offender Reentry [DRAOR]) alongside PCRA for people who were in the red band category. (For more information on U.S. federal probation's five color-ordered risk scheme, see AO, 2023). We explored the feasibility and value of adding DRAOR, reassessed monthly, to existing risk assessment procedures for red band status individuals under federal supervision in the community. Previous research suggests that DRAOR scores predict recidivism incremental to well-validated measures of criminal history and/or stable criminogenic needs (Coulter & Lloyd, 2023; Lloyd et al., 2020) and that key predictive validity effects remain consistent across demographic groups (e.g., race/ethnicity and gender; Coulter et al., 2023; Scanlan et al., 2020). To extend these findings to the federal probation context, we explored (1) whether monthly repeat assessment of DRAOR subscales improved recidivism prediction incremental to PCRA scores, and (2) whether DRAOR prediction performed similarly across demographic groups and probation officers.

#### Method

Sample

U.S. probation officers (USPOs) at the Western District of Oklahoma recorded data used in this study over 29 months, from November 1, 2017, to April 14, 2020. In this period, 27 supervision officers conducted 378 PCRA assessments (approximately every 6 months) and 2,024 DRAOR assessments (approximately monthly) for 244 individuals on federal supervision orders who were placed in the red band category. These 244 individuals were primarily male (90.6 percent). At start of supervision, average age was 38.2 years (SD = 9.21; range = 20-66). File records listed participants' ethnicities as White (42.6 percent), Black (38.9 percent), Hispanic (9.0 percent), Indigenous (e.g., Alaskan Native; 7.8 percent), or other/unknown (1.6 percent). File records listed most participants' marital status as single (58.2 percent) with the remainder married or cohabitating (20.5 percent), divorced or separated (20.1 percent), widowed (0 percent), or unknown (0.8 percent).

USPOs only completed DRAOR assessments when individuals had "red band" status (PCRA scores 10 or greater, except for 8 individuals in this sample with PCRA scores lower than 10 who were given an "override" to red band status). During the study time frame, individuals' red band status could change.

USPOs scored DRAOR only at the time that individuals had red band status, with some individuals cycling on and off red band status during the study. Giving more attention to higher risk individuals is strongly consistent with the risk-need-responsivity framework (Bonta & Andrews, 2023), and consistent with findings from other jurisdictions that show the presence of acute dynamic risk factors is relatively more concerning among people with higher long-term risk (e.g., Stone et al., 2024). In this sample, the average PCRA score at the time of the first recorded DRAOR assessment was M = 12.54 (SD = 2.19; range = 10-17, excluding the 18 PCRA assessments conducted on the 8 override cases). For comparison, a routine federal sample's average PCRA score was M = 6.33 (SD = 3.43; range = 0-18; Lowenkamp et al., 2015). In the present sample, participants' current convictions were for weapon possession (29.5 percent), or for substance-related (23.7 percent), non-sexually violent (16.5 percent), non-violent (e.g., financial crimes; 10.4 percent), sexual (2.9 percent), failure to register (6.5 percent), or other (e.g., technical violations or missing information; 10.5 percent) crimes.

#### Measures

Our implementation partner at Western District of Oklahoma extracted file information for each participant, including demographic information (date of birth, ethnicity, marital status, and gender), supervision start and end dates, new revocations and arrests, and PCRA scores. We coded recidivism as any new recidivism (revocations, new arrests, charges, and convictions), new criminal recidivism (new arrests, charges, and convictions, excluding revocations) and violent recidivism (new arrests or charges for a violent crime, e.g., weapon possession, threats, and assault, but excluding four sexual recidivism events that were each related to accessing child sexual exploitation material).

In analyses examining dynamic change in PCRA scores, we used the sum of all 15 scored items of PCRA 2.0 (AO, 2018) that assess criminal history, education/employment, substance abuse, social networks, and cognitions. In other prediction analyses, we used the sum of only the 6 criminal history items. Because this study restricted the sample to red band cases (i.e., limiting sample PCRA scores to the 10-18 range), results presented here do not represent PCRA's overall performance for predicting recidivism. To account for the restricted range of PCRA scores, we entered

only the criminal history scores. Total PCRA scores discriminate 1-year general recidivism (i.e., new arrest) from non-recidivism (AUC = .73) and 1-year violent recidivism from no violent recidivism (AUC = .76; Lowenkamp et al., 2015).

There are three conceptually distinct subscales (Stable, Acute, and Protect) within the 19 items of Dynamic Risk Assessment for Offender Reentry (DRAOR; Serin, 2007). The 6 items on DRAOR Stable assess criminogenic needs over 3 months (antisocial attitudes, traits, and behavior patterns). The 7 items on DRAOR Acute assess life de-stabilizers (substance misuse, emotions, and situational factors) at the present time, or since the last contact. For DRAOR Stable and Acute subscales, users score each item not a problem (0), slight/possible problem (1), or definite problem (2), for a maximum score of 12 and 14, respectively. Designed to measure strengths, the 6 items on DRAOR Protect assess prosocial perceptions and prosocial relationships over 3 months, scored as not an asset (0), slight/possible asset (1), or definite asset (2), for a maximum score of 12. The intention is that DRAOR should always be an "add on" to a more comprehensive, longer-term risk tool, by nature of its shorter-term focus and regular but brief reassessment. Up-to-date DRAOR subscale scores predict general and violent recidivism above risk tools assessing criminal history and criminogenic needs (e.g., see Coulter & Lloyd, 2023; Lloyd et al., 2020; Stone et al., 2021).

#### Analytic Plan

We used Cox regression survival analysis with time-varying predictors (see Singer & Willett, 2003). This statistical model uses all data throughout supervision by updating risk assessment information across time. Thus, the model always uses the most recent score to predict recidivism and accounts for any gaps when individuals no longer had red band status (i.e., there were no DRAOR scores for a period of time). In the sample of 244 people, supervision ended for 32 people (e.g., for a revocation), then a new supervision order began. For two people, there were three supervision orders in the 29-month time frame. As others have done (see Howard & Dixon, 2013; Lloyd et al., 2020), we retained and analyzed all 278 supervision periods as the unit of analysis.

First, we tested if updated reassessment scores from PCRA, DRAOR Stable, DRAOR Acute, or DRAOR Protect improved prediction

beyond the first assessment scores using these same scales. These models test whether reassessment adds value for prediction beyond the first assessed score. The outcomes were any, criminal, or violent recidivism, resulting in 12 prediction models (i.e., associations between four scales and three types of recidivism). To allow PCRA scores to update with time, we used total PCRA scores (i.e., including dynamic items) for this analysis.

Next, we tested another 12 models to examine whether DRAOR adds incremental prediction beyond PCRA criminal history scores (with all scores updating in the models across time, including PCRA criminal history scores, when scoring may have changed after new offending events). We first examined PCRA criminal history scores as the only predictor of any, criminal, or violent recidivism. We then tested combinations of PCRA criminal history scores and DRAOR subscales (i.e., PCRA + DRAOR Stable, PCRA + DRAOR Acute, and PCRA + DRAOR Protect) for each type of recidivism.

For model interpretation, we present Harrell's c (Harrell et al., 1982), also called c-index (Heagerty & Zheng, 2005). This prediction effect size is closely similar to the Area Under the Curve (AUC) statistic. Unlike the AUC, c takes follow-up time into account, but, just like the AUC, c represents the probability that a randomly selected person who recidivated had a higher score than a randomly selected person who did not recidivate (e.g., .70 means in 70 percent of comparisons a randomly selected recidivist will have a higher score than a randomly selected non-recidivist). By taking time into account, a c-index is typically smaller than a similar AUC, but, importantly, both AUC and c are smaller when samples have a narrower range of scores (e.g., the 10-17 range of PCRA scores in this study's "red band" sample) versus a wider range (e.g., the full possible range of 0-18; see Hanson, 2008, 2022). For these reasons, PCRA prediction effects in this sample will appear smaller than effects reported in other studies. Rice and Harris's (2005) guidelines consider c-indices of .56, .64, and .71 to be small, medium, and large effects, respectively.

Finally, we tested whether prediction (associations between DRAOR scores and recidivism) remained the same across participants of different race/ethnicity, across male and female participants, and across the supervision officers who recorded scores. We used a multilevel Cox regression model that adapts this prediction model to include groupings

(i.e., allowing score-recidivism relationships to vary by race/ethnicity, gender, or officer, to see if effects indeed varied by demographic group or supervision officer).

#### Results

Average DRAOR Scores and Correlations

At the first recorded DRAOR assessment of each supervision order (n = 278), the average DRAOR Stable score was M = 5.65 (SD = 2.87) out of 12 possible points, with a correlation of r = .31 with the most recently recorded PCRA score. The average DRAOR Acute score was M = 3.71 (SD = 2.72) out of 14 possible points, with a correlation of r = .39 with PCRA scores. The average DRAOR Protect score was M =5.62 (SD = 3.01) out of 12 possible points, with a correlation of r = -.36 with PCRA scores.

DRAOR Stable and Acute scores correlated at r = .63. DRAOR Stable and Protect scores correlated at r = -.64. DRAOR Protect and Acute scores correlated at r = -.47.

#### Recidivism Prediction

The average follow-up time from start of supervision to end of observation was M =15.4 months (SD = 12.4; range = 24 days to 7.3 years). Of the 278 supervision orders, 126 ended with recidivism (45.3 percent of all orders, including 79 revocations). The remaining 47 events were criminal recidivism (16.9 percent of all orders), and 21 of these 47 events were charges for violent crimes (7.6 percent of all orders).

In Table 2, we show the 7 out of 12 models where reassessment improved recidivism prediction after accounting for the first recorded assessment score. For any recidivism (including revocations), all four tools (PCRA, DRAOR Stable, Acute, and Protect) showed enhanced prediction effects upon reassessment. For criminal recidivism outcomes (excluding revocations), DRAOR Acute and Protect subscales showed improved prediction on reassessment. Finally, for violent outcomes, only DRAOR Acute reassessments improved prediction of violence beyond the initial DRAOR Acute score, showing that as supervision officers kept acute dynamic risk information up-to-date each month, updated DRAOR Acute scores demonstrated enhanced prediction of imminent violent recidivism (i.e., within the next month). Regularly updating PCRA, DRAOR Stable, or DRAOR Protect scores in the time frame of this study did not enhance prediction of imminent violent recidivism.

As shown in Table 3, PCRA criminal history scores were associated with any recidivism (including revocations, c-index = .59) and criminal recidivism (excluding revocations, c-index = .63) outcomes to a statistically significant degree. These effects are approximately moderate. In this sample, PCRA criminal history scores were not associated with violent recidivism to a statistically significant degree, with a small prediction effect (c-index = .55).

Adding DRAOR subscale scores into the prediction models with PCRA criminal history scores improved prediction (Table 3). When predicting either any recidivism (including revocations) or criminal recidivism (excluding revocations), scores from all three DRAOR subscales and PCRA criminal history were significantly associated with recidivism, increasing the effect sizes above moderate toward large (c-index = .67 to .77). However, only DRAOR Acute scores were related to violent recidivism. Prediction models with DRAOR Acute achieved the highest effect sizes when predicting criminal recidivism (c-index = .70) and when predicting violent recidivism (c-index = .67), both with moderate-to-large effect sizes.

#### Recidivism Prediction by Group

The core purpose of the models shown in Table 4 was to examine whether the relationship between DRAOR scores and any recidivism (including revocations) might be stronger or weaker in some demographic groups. We also tested whether prediction effects were consistent across supervision officers. The models in Table 4 show no clear evidence of differences in recidivism prediction across gender, race/ethnicity, or supervision officer.

These models show there are different recidivism rates associated with men compared to women. These models also show supervision officers' caseloads have different average recidivism rates (i.e., some officers have higher versus lower risk caseloads). However, differences in DRAOR Acute scores appear to explain the different recidivism rates across gender and officer caseload, and, importantly, prediction effects did not differ by gender or supervision officer (or race/ ethnicity). In other words, the most complex models tested if prediction was enhanced or reduced across different groups, but there were no substantial differences in prediction effects (as seen in the statistically non-significant  $\chi^2 \Delta$  values).

#### Discussion

The results of this study add to a growing body of research in community corrections that shows a well-rounded assessment strategy considers risk domains from multiple perspectives, such as using tools that document criminal history, criminogenic needs, acute dynamic risk factors, and strengths. Results also supported the value of ongoing reassessment to ensure officers have sufficiently updated knowledge of current risk. Specifically, supplementing reassessed PCRA scores with reassessments from the three DRAOR subscales extended officers' knowledge beyond identifying who is likely to have a new criminal arrest or charge, to identify when an individual was most likely to have a new criminal arrest or charge (i.e., in the next month). When considering new arrests and charges for violence, combining the

DRAOR Acute subscale with PCRA criminal history scores additionally identified when an individual was most likely at risk for imminent violence. Importantly, there was no evidence in this sample that DRAOR prediction was dissimilar across participants of different genders or race/ethnicities, nor across caseloads assessed by different supervision officers. This suggests DRAOR was implemented with sufficient fidelity in a federal probation context, and using DRAOR did not disadvantage any one demographic group in the Western District of Oklahoma in terms of identifying who was presently at higher versus lower risk.

This study's finding that supplementing PCRA with an assessment of acute dynamic risk factors improves prospective prediction of violence supports similar conclusions based on retrospective analyses (Lowenkamp

TABLE 2
Predicting recidivism outcomes, simultaneously using both the client's first PCRA (or DRAOR) score of the supervision period and the client's most up-to-date PCRA (or DRAOR) score

Predictor	b (SE)	<i>p</i> -value						
Any recidivism outcome (including revocations)								
1. First PCRA score	-0.08 (0.14)	.58						
Updated PCRA scores	0.33 (0.14)	.02						
2. First DRAOR Stable score	-0.03 (0.04)	.54						
Updated DRAOR Stable scores	0.29 (0.04)	< .001						
3. First DRAOR Acute score	0.01 (0.04)	.78						
Updated DRAOR Acute scores	0.30 (0.03)	< .001						
4. First DRAOR Protect score	0.05 (0.04)	.21						
Updated DRAOR Protect scores	-0.27 (0.04)	< .001						
Criminal recidivism only								
5.First DRAOR Acute score	0.08 (0.06)	.18						
Updated DRAOR Acute scores	0.13 (0.06)	.03						
6.First DRAOR Protect score	0.07 (0.07)	.31						
Updated DRAOR Protect scores	-0.17 (0.07)	.01						
Violent recidivism only								
7.First DRAOR Acute score	-0.01 (0.10)	.90						
Updated DRAOR Acute scores	0.19 (0.09)	.05						

Note. PCRA = Post Conviction Risk Assessment risk tool. DRAOR = Dynamic Risk Assessment for Offender Reentry risk tool. N = 378 PCRA assessments and 2,024 DRAOR assessments across 278 supervision orders. All recidivism outcomes = 126 events, criminal recidivism outcomes = 47 events, violent recidivism outcomes = 21 events. This table presents prediction models where the addition of updated scores resulted in prediction at p = .05. The coefficient for prediction of criminal recidivism using updated DRAOR Stable scores after controlling for first DRAOR Stable score resulted in p = .06. Results from the remaining five prediction models not displayed are available by contacting the first author.

TABLE 3
Predicting future recidivism (revocations and new crimes),
criminal recidivism, and violent recidivism using the most up-todate PCRA score and most up-to-date DRAOR score

Predictor	b (SE)	Exp( <i>b</i> )	<i>p</i> -value	c index						
Any recidivism outcome (including revocations)										
1. PCRA Criminal History score	0.35 (0.11)	1.42	< .001	0.59						
2. PCRA Criminal History score	0.25 (0.10)	1.29	.02	0.74						
DRAOR Stable score	0.26 (0.03)	1.29	< .001							
3. PCRA Criminal History score	0.31 (0.11)	1.36	.005	0.77						
DRAOR Acute score	0.30 (0.03)	1.34	< .001	0.77						
DRAOR Acute score	0.30 (0.03)	1.54	< .001							
4. PCRA Criminal History score	0.31 (0.10)	1.37	.002	0.72						
DRAOR Protect score	-0.22 (0.03)	0.80	< .001							
	Criminal recidivism on	ly								
5. PCRA Criminal History score	0.58 (0.19)	1.79	.002	0.63						
6. PCRA Criminal History score	0.53 (0.18)	1.69	.004	0.68						
DRAOR Stable score	0.12 (0.05)	1.13	.01							
7. PCRA Criminal History score	0.57 (0.19)	1.77	.002	0.70						
DRAOR Acute score	0.17 (0.05)	1.18	< .001							
	()									
8. PCRA Criminal History score	0.55 (0.18)	1.74	.003	0.67						
DRAOR Protect score	-0.12 (0.05)	0.89	.02							
O DCDA Criminal History	Violent recidivism	1 21	4.4	0.55						
9. PCRA Criminal History score	0.19 (0.25)	1.21	.44	0.55						
10. PCRA Criminal History score	0.19 (0.25)	1.21	.45	0.58						
DRAOR Stable score	0.05 (0.07)	1.05	.54							
	, ,									
11. PCRA Criminal History score	0.18 (0.26)	1.20	.48	0.67						
DRAOR Acute score	0.18 (0.07)	1.19	.02							
12. PCRA Criminal History score	0.19 (0.25)	1.21	.45	0.58						
DRAOR Protect score	-0.09 (0.07)	0.91	.23							

Note. PCRA = Post Conviction Risk Assessment risk tool. DRAOR = Dynamic Risk Assessment for Offender Reentry risk tool. c-index is Harrell's c (Harrell et al., 1982; calculated via Heagerty & Zheng, 2005). N = 378 PCRA assessments and 2,024 DRAOR assessments across 278 supervision orders. All recidivism outcomes = 126 events, criminal recidivism outcomes = 47 events, violent recidivism outcomes = 21 events. When using the full PCRA score in these models, the pattern of statistically significant results remained the same for predicting any recidivism and violent recidivism. For predicting criminal recidivism, total PCRA scores did not predict criminal recidivism to a statistically significant degree when controlling for DRAOR scores, and DRAOR Protect scores did not predict criminal recidivism to a statistically significant degree when controlling for total PCRA scores. These alternate prediction models are available by contacting the first author.

et al., 2016). Both studies concluded that DRAOR Acute risk factors were relevant for determining the likelihood and timing of violent recidivism. This conclusion is also consistent with research in several other jurisdictions worldwide, where DRAOR Acute is more closely associated with imminent recidivism and imminent violence compared to the other DRAOR subscales (e.g., Coulter & Lloyd, 2023; Davies et al., 2022; Lloyd et al., 2020, Stone et al., 2021). Collectively, a growing body of literature in community corrections indicates routine reassessment of dynamic risk factors provides meaningful information for case management, whether adopting tools designed to predict short-term general recidivism, violent recidivism, and/or sexual recidivism.

Although the sample size for this study was relatively small (i.e., 244 people), a strength of this study was that the sample represented a complete population of "red band" cases across about a 2-year period in one federal district. By incorporating a substantial number of PCRA and DRAOR reassessments, analyses shed light on how to combine these tools to predict the *timing* of recidivism among the highest risk cohort of people when the recidivism outcome is still unknown (i.e., prospectively predict within routine community supervision).

Although the present findings are promising, they should be viewed as preliminary, requiring replication in other federal districts and with larger samples. Prediction effects may not be the same among lower risk samples or in different districts or jurisdictions. Further, this study was limited in examining prediction of recidivism without incorporating information about how supervision officers simultaneously intervened to address and manage criminogenic needs and acute dynamic risk factors. It is necessary to consider intervention and its effects to better understand how risk assessment supports effective case management and supervision officer decision-making. Future studies may benefit from testing how supervision officers respond to elevations in assessed risk and whether and to what extent interventions informed by risk assessment are associated with reduced recidivism.

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TABLE 4. Predicting future recidivism using the most up-to-date DRAOR score, while testing whether the relationship between DRAOR scores and recidivism significantly varied across groups (gender, ethnicity, and supervision officer)

	Ungrouped Predictor Model		Recidivism Base Rate Can Vary by Group (Random Intercept Model)		Predictor-Recidivism Relationship Can Vary by Group (Random Intercept and Random Slope Model)				
Variable	b (SE)	Exp(b)	b (SE)	Exp(b)	b (SE)	Exp(b)			
Any recidivism outcome, results grouped by gender (male or female)									
DRAOR Stable	0.27 (0.03)	1.31	0.27 (0.03)	1.31	0.27 (0.03)	1.31			
χ2 Δ from prior model	-	-	$\chi 2 \Delta = 4$	.55*	$\chi 2 \Delta = 0$	.01			
DRAOR Acute	0.31 (0.03)	1.36	0.30 (0.03)	1.35	0.31 (0.04)	1.36			
χ2 Δ from prior model	-	-	$\chi 2 \Delta = 2$	2.43	$\chi 2 \Delta = 2$	.55			
DRAOR Protect	-0.23 (0.03)	0.79	-0.23 (0.03)	0.79	-0.24 (0.03)	0.79			
χ2 Δ from prior model	-	-	$\chi 2 \Delta = 5.93^{**}$		$\chi 2 \; \Delta = 0.49$				
Any recidivism outcome, results grouped by ethnicity (White, Black, Hispanic, Indigenous, Other / Unknown)									
DRAOR Stable	0.27 (0.03)	1.31	0.27 (0.03)	1.31	0.27 (0.03)	1.31			
$\chi 2$ $\Delta$ from prior model	-	-	$\chi 2 \Delta = 0$	).45	$\chi 2 \Delta = 0.$	001			
DRAOR Acute	0.31 (0.03)	1.36	0.31 (0.03)	1.36	0.30 (0.03)	1.36			
$\chi^2$ $\Delta$ from prior model	-	-	$\chi 2 \Delta = 0$	).01	$\chi 2 \Delta = 1$	.57			
DRAOR Protect	-0.23 (0.03)	0.79	-0.23 (0.03)	0.79	-0.23 (0.03)	0.79			
$\chi 2 \Delta$ from prior model	-	-	$\chi 2 \Delta = 0$	0.03	$\chi 2 \Delta = 0.$	005			
Any recidivism outcome, results grouped by supervision officer (27 USPOs)									
DRAOR Stable	0.27 (0.03)	1.31	0.29 (0.03)	1.34	0.29 (0.03)	1.34			
$\chi 2$ $\Delta$ from prior model	-	-	$\chi 2 \Delta = 7.$	49**	$\chi 2 \Delta = 0$	.02			
DRAOR Acute	0.31 (0.03)	1.36	0.31 (0.03)	1.37	0.31 (0.03)	1.37			
$\chi$ 2 Δ from prior model	-	-	$\chi 2 \Delta = 3$	3.79	$\chi 2 \Delta = 0$	.00			
DRAOR Protect	-0.23 (0.03)	0.79	-0.26 (0.03)	0.77	-0.27 (0.04)	0.77			
$\chi 2 \Delta$ from prior model	-	-	$\chi 2 \Delta = 10$	.63**	$\chi 2 \Delta = 0$	.09			

Note. DRAOR = Dynamic Risk Assessment for Offender Reentry risk tool. N = 2,024 DRAOR assessments across 278 supervision orders. Any recidivism outcomes = 126 events.