Enhancing Community Supervision Through the Application of Dynamic Risk Assessment

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RISK FACTORS HAVE commonly been distinguished as being either static (e.g., age at first arrest, number of prior convictions) or dynamic (e.g., substance use, employment status). In the early days of risk assessment (1970s), static factors were most commonly incorporated into risk measures. They were easy to code and readily available; most importantly, these initial static risk measures demonstrated accuracy equal to or greater than unstructured assessments (Grove, Zald, Lebow, Snitz, & Nelson, 2000). Importantly, by the early 1980s, opposition to measures with exclusively static risk factors was beginning to develop, primarily because these scales could not identify intervention targets, and if scores could change, the range of potential change was greatly restricted and unidirectional (i.e., clients could only be rated worse; Bonta, 1996; Wong & Gordon, 2006). Notably, involvement in treatment could not improve scores, leading to the problematic practice of treatment completion having no impact on an individual's predicted outcome.

Andrews and Bonta (2010) presented a hierarchy of risk factors intended to identify appropriate targets for rehabilitation programs; their choice of variables was consistent with a conceptualization of dynamic risk factors as relatively slow-evolving features. Their description of these targets as *criminogenic needs* came to be considered synonymous with the concept of dynamic risk and led to the risk and need principles. Indeed these stable dynamic risks were increasingly common in risk and need measures; their inclusion was intended to inform both levels of risk and case planning requirements for clients. Clients with a greater number of stable dynamic risks (i.e., criminogenic needs) were considered higher risk, warranting more intensive intervention and level of service. Encouragingly, targeting these criminogenic needs leads to improved client outcomes (Aos, Miller, & Drake, 2006; Smith, Gendreau, & Swartz, 2009).

The PCRA is a contemporary risk and need instrument similar to other measures such as the LS/CMI, the COMPAS, and the ORAS. Validity research indicates the PCRA has comparable or superior predictive accuracy to these other instruments (Desmarais & Singh, 2013). Importantly, even though the PCRA assessment is done at baseline, at 6 months, and then yearly thereafter, change scores across time on the PCRA are related to client outcome (Cohen, Lowenkamp, & VanBenschoten, 2016; Luallen, Radakrishnan, & Rhodes, 2016). The odds of client failure can be predicted by changes from one PCRA assessment to the next. For instance, in a case where the client's PCRA score is 3 points *lower*, the probability of violent rearrest is *decreased* by 19 percent. In contrast, in a case where the client's PCRA score is 3 points *higher*, the probability of violent rearrest is *increased* by 31 percent. Clearly, change on criminogenic needs, as measure by the PCRA, is important in understanding client outcome.

Increasingly, experts in the risk assessment field have argued that accuracy regarding the timing of client outcome can be enhanced by considering changes in *acute* dynamic risk factors (Douglas & Skeem, 2005; Serin, Chadwick, & Lloyd, 2016). Specifically, the expectation is that acute risks flag imminence of problematic outcomes for clients and augment risk assessment beyond static factors. As well, elevations in acute risk should mean that clients with similar crimes and PCRA scores could be managed differently from clients without such acute risks. Several examples illustrate this viewpoint. You have a client for whom employment has been a concern in that when unemployed, the client commonly turns to criminal behavior to generate income. Hence, when that client advises you that he or she has just been fired, this should be a flag that increased monitoring (e.g., efforts to secure a new job, assistance with job search, access to and association with criminal peers, etc.) is in order. Similarly, if a client during a session reports (or you observe) increases in anger or negative emotions, this might indicate increased vulnerability to criminal thinking and criminal behavior. Such a change could warrant further scrutiny and intervention by officers.

Despite decades of risk assessment research, the field is limited in its understanding of the immediate features (whether situational or intrapersonal) that influence an individual to take criminal action (Farrington,

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2011; Yang & Mulvey, 2012) or forgo criminal action when presented with an opportunity for crime (i.e., crime desistance; Maruna, 2010). The current research was undertaken to examine whether certain acute dynamic risks might better identify not only which clients are at risk but also *when* that risk might be most elevated for a particular client. In this manner, it is possible for officers to consider risk at the case level and intervene accordingly to mitigate it.

Fortunately, some recent research regarding acute dynamic risk is available (Serin, Chadwick, & Lloyd, 2015). Using the list of acute variables developed by Serin (2007) in the Dynamic Risk Assessment for Offender Reentry (DRAOR) measure, the present study examines if key acute risks forecast violent rearrest in a federal probation sample. The results may have implications for officer assessment and intervention strategies.

Methods

Sample

Data used for this study were assembled from federal supervision records from the Probation and Pretrial Services Office's internal case management database system (Probation and Pretrial Services Automated Case Tracking System or PACTS) and other extant data sources. The source dataset included 385,130 offenders serving either a term of probation or a term of supervised release (TSR) that commenced between October 1, 2004, and September 30, 2013. Excluded from the source dataset were offenders who were deported, serving a sentence in another jurisdiction, or otherwise unavailable for supervision.

A sample of 2,153 offenders who had been arrested for a violent offense (i.e., homicide, attempted homicide, sexual assault, robbery, and felonious assault) while under supervision was extrapolated from the source dataset. Another 1,963 cases were selected that were not arrested for a violent offense while on supervision but matched the sample of violent offenders based on supervision district, convicted offense, risk score, and year supervision began. This provided a sample of 4,116 cases.

Data collection for this study occurred over the course of two weeks in September 2014. Officers used available electronic data including presentence reports, federal Bureau of Prisons (BOP) data, and PACTS data to complete the data collection forms. Forty-seven officers ranging in experience from 5 years to 23 years collected data during the weeks of September 15-19 and September 22-26. One week prior to data collection, officers were given copies of the data collection form and the coding manual. A WebEx training was also conducted to provide an overview of the study and a detailed review of the data collection form and coding manual. The 47 officers assisted in the collection of data on 949 cases.

TABLE 1.
Distribution of Cases for Total Sample and Sample Collected in September 2014

	Total Sample		Sept, 2014 Sample	
	N	%	N	%
Homicide	696	17	258	27
Sexual assault	158	4	48	5
Robbery	533	13	151	16
Felonious assault	766	19	198	21
Comparison cases	1963	48	294	31
Total	**4116**	**100**	**949**	**100**

Experienced data quality analysts were used for quality assurance and data entry. The data quality analysts reviewed each completed data collection form for accuracy, then entered the data into a web-based version of the data collection form. The distribution of the cases for the entire sample and the cases where data were collected are listed in Table 1.

Measures

Offender data included prior criminal history, information related to imprisonment in the Federal Bureau of Prisons, current offense, needs while under supervision, and information on the violent offense committed while under supervision. The "needs while under supervision" information was collected using the Dynamic Risk Assessment for Offender Reentry (DRAOR) developed by Serin (2007) and the Two Tiered Risk Assessment (TTR) developed by Mills, Kroner, and Morgan (2011). However, the current study only uses the data on the DRAOR.

The DRAOR comprises 19 items divided into three subscales: stable factors, acute factors, and protective factors. This study used the seven acute factors: substance abuse, anger/hostility, opportunity/access to victims, negative mood, employment, interpersonal relationships, and living situation. Each item is rated using a three-point scoring format (0, 1, 2) that corresponds to anchors of "not a problem," "slight/possible problem," and "definite problem." When summed, the seven items create a score ranging from zero to 14, with higher scores indicating a greater number and/or degree of problems present for the assessment time period.

Data on acute factors were coded in 30-day increments for up to 18 months. If supervision spanned more than 18 months, then the first 6 months of supervision and the 12 months preceding the violent arrest or the end of supervision were coded. Data on violations of supervision conditions such as new arrests, job changes, travels outside jurisdiction without permission, treatment noncompliance, positive drug tests, and failure to report were also coded in 30-day increments. A total of 13,676 observational periods were coded for the 949 offenders. Due to the nature of the data collection, there were varying levels of missing data that were replaced with the most recent value recorded for a particular measure. The use of Cox Regression models produced a total of 597 cases with usable data, of which 392 cases were arrested for a violent offense while under supervision. There was a total of 7,538 observation periods associated with these 597 cases.

In addition to the DRAOR, a violence classifier was developed to capture an offender's risk for committing a violent offense. Offenders were considered at higher risk for violence if they had a PCRA score greater than eight or a PCRA score less than nine with two or more of the following factors present: gang affiliation, currently on supervision for a sex or violent offense, history of drug arrests, history of firearms arrests, or a history of arrests for violence. Finally, a dichotomous variable (early onset) was developed that had a value of zero if the offender's first arrest was at age 18 or greater and a value of one if the offender's first arrest was before the age of 18.

Analyses

Bivariate and multivariate statistics were estimated during the analysis phase of the study. Since there were different lengths of supervision, and since the violent arrest of interest in most instances stopped the collection of data, we opted to focus on survival analysis models. In addition to the DRAOR scales, the violence classifier and early onset variables were also used in the multivariate Cox Regression (survival analysis) models.

Results

The first Cox Regression model included the violence classifier, the early onset variable, and the DRAOR acute item score. The results of that model are contained in Table 2 and indicate that once the dynamic acute risk factors are taken into account, the effect of the violence classifier, a static measure, is reduced to non-significance. The measure of early onset continues to be a predictor of time to failure. The DRAOR Acute Score is a significant predictor of failure once the score reaches a value of four or greater. Note that the hazard ratios for the acute score tend to follow an upward trend indicating that, in general, as the score increases so too does the likelihood that failure occurs in the near term.

The DRAOR Acute Score was recoded into three categories (0-4, 5-10, and 11-14). These categories were then used to display the differences in survival rates based on the accumulation of acute risk factors. As indicated in Figure 1 (see last page of article), those with scores between zero and four demonstrate the highest survival rates. Those with scores between five and ten survive at a noticeably lower rate than those with lower scores. Finally, those with scores between 11 and 14 clearly have the lowest survival rates and the decrease in survival rates is, relatively, very steep.

In an effort to determine if any particular acute risk factor was a better predictor of arrest for violence than the others, a model using each of the acute risk factors as predictors, rather than the summed DRAOR Acute Score, was constructed and estimated. The results of those analyses are contained in Table 3 and indicate that three factors were significantly related to time to failure (arrest for a violent offense). Those three factors are anger/hostility, access to victims, and negative mood.

A figure displaying the survival curves for each value (0=not a problem;1=possible/slight problem; 2=definite problem) of each of the significant factors was created. These are displayed in Figures 2 through 4 (see last page of article). Figures 2 and 3 demonstrate that the survival rates drop as the ratings for anger/hostility and opportunity/victim access increase from no problem to slight/possible problem and also when an offender was ranked as having a definite problem. In Figure 4, which plots the survival curves for the different ratings of negative mood, the separation between slight/possible problem and definite problem is not as pronounced as in Figures 2 and 3. In addition, in Table 3 the hazard ratio for definite problem for negative mood is not statistically significant. It is, however, clear that as the rating for negative mood shifts from no problem to slight/possible problem, a statistically significant hazard ratio is generated.

Discussion

The findings are very encouraging and inform refinements to the risk assessment process. Despite being an archival study that may be limited due to the availability of information necessary to code acute risk, 3 of the 7 acute risks identify cases that have a greater likelihood of violent rearrest in a large sample of seriously violent clients. Problems and concerns relating to anger/hostility, victim access, and negative mood all had significant odds ratios. Specifically, the results indicate elevations on these acute risks increased the

TABLE 2.
Cox Regression Predicting Arrest Using Violence Classifier, Early Onset, and DRAOR Acute Score

Variable	Hazard Ratio	p value	95% CI Lower	95% CI Upper
Violence Classifier	1.13	0.42	0.84	1.53
Early Onset	1.45	0.00	1.14	1.84
Monthly Acute Factor				
1	1.24	0.60	0.56	2.74
2	1.67	0.15	0.84	3.33
3	2.07	0.02	1.12	3.83
4	2.62	0.00	1.48	4.66
5	6.31	0.00	3.78	10.52
6	5.33	0.00	3.27	8.68
7	5.06	0.00	2.84	9.00
8	12.16	0.00	6.83	21.63
9	10.94	0.00	6.65	17.99
10	6.88	0.00	3.93	12.03
11	9.88	0.00	5.67	17.23
12	11.71	0.00	6.79	20.18

TABLE 3.
Cox Regression Predicting Arrest for Violence Offense with Violence Classifier, Early Onset, and Each DRAOR Acute Factor

	Hazard Ratio	p value	95% CI Lower	95% CI Upper
Violence Classifier 2	1.17	0.31	0.86	1.60
Early Onset	1.29	0.04	1.01	1.63
Substance Abuse				
Slight/Possible Problem	0.84	0.24	0.62	1.12
Definite Problem	0.90	0.57	0.64	1.28
Anger/Hostility				
Slight/Possible Problem	**1.90**	**0.00**	**1.28**	**2.81**
Definite Problem	**3.08**	**0.00**	**1.81**	**5.26**
Victim Access				
Slight/Possible Problem	**1.60**	**0.01**	**1.13**	**2.26**
Definite Problem	**3.04**	**0.00**	**2.00**	**4.63**
Negative Mood				
Slight/Possible Problem	**1.41**	**0.05**	**0.99**	**2.00**
Definite Problem	**1.45**	**0.15**	**0.88**	**2.39**
Employment				
Slight/Possible Problem	1.07	0.66	0.78	1.48
Definite Problem	1.00	0.99	0.73	1.36
Interpersonal Relationships				
Slight/Possible Problem	1.03	0.84	0.74	1.44
Definite Problem	1.12	0.61	0.73	1.69
Living Situation				
Slight/Possible Problem	0.66	0.02	0.47	0.93
Definite Problem	1.17	0.45	0.77	1.78

likelihood of a violent rearrest by 26 percent, 25 percent, and 9 percent respectively. As well, overall, a higher acute risk score significantly increased the odds of violent rearrest.

Equally informative is what did *not* relate to risk of violent rearrest. Substance abuse, employment, interpersonal problems, and living situation failed to inform the likelihood of violent rearrest. Moreover, PCRA elevated score (e.g., violence classifier) did not increase the likelihood of violent rearrest.

In addition to the likelihood of violent rearrest, the current study addresses the timing of such rearrest across risk groups. The survival analyses reflect extremely steep slopes for clients with significant problems relating to acute risk and specifically for anger/hostility, victim access, and negative mood. This means that these clients fail significantly more often and more quickly. With heightened degrees of imminent risk, immediate and appropriate changes in supervision strategies can be made to address the risk to reoffend and potential risk of harm to the community.

Despite these promising findings, some caution is warranted. This was a retrospective study that relied on existing information reflected in client chronos. Replication in a prospective study is warranted. Acute risk factors can change very quickly and should be consistently addressed with higher-risk individuals in order to enhance decision making, provide adequate interventions, and improve client outcomes (Serin et al., 2016). As well, additional acute dynamic risk factors that were not included in this study may also inform the likelihood and timing of client violent rearrest. Work to expand the inventory of credible predictors should be encouraged. Finally, risk recognition through the inclusion of acute dynamic risk, while helpful for officers, is somewhat limiting without the provision of best practice approaches for officers to use when these clients and their acute risk are identified. Fortunately, this work has begun in the upcoming PCRA 2.0 training, in which officers are provided with more specific approaches to manage clients who are considered at higher risk for violence while on probation.

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FIGURE 1.
Survival Curves by DRAOR Acute Score

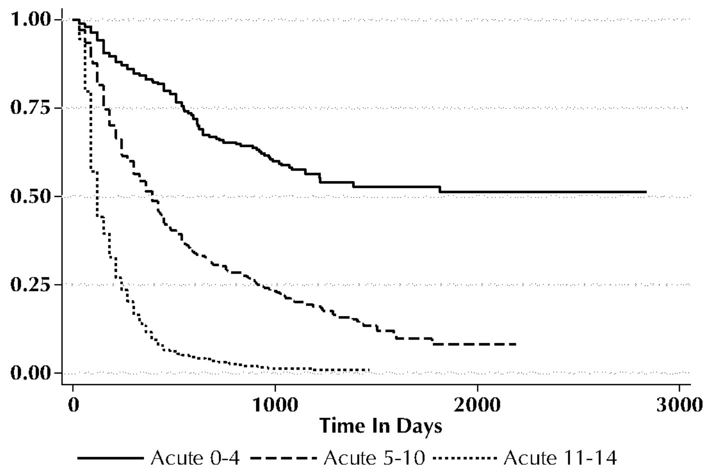

FIGURE 2.
Survival Curves by DRAOR Acute Anger/Hostility Rating

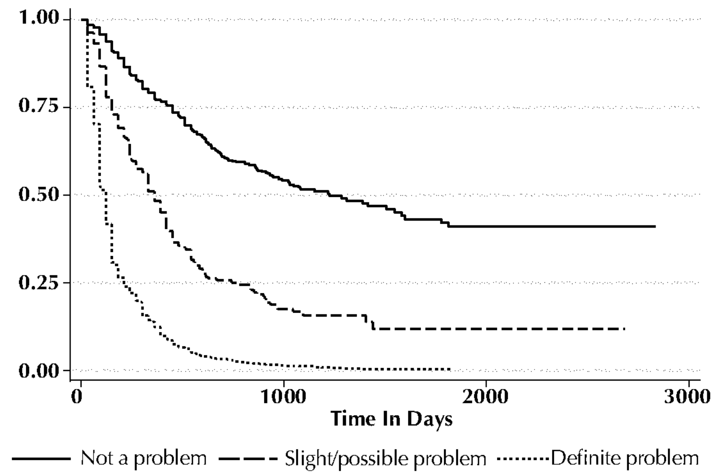

FIGURE 3.
Survival Curves by DRAOR Acute Opportunity/Victim Access Rating

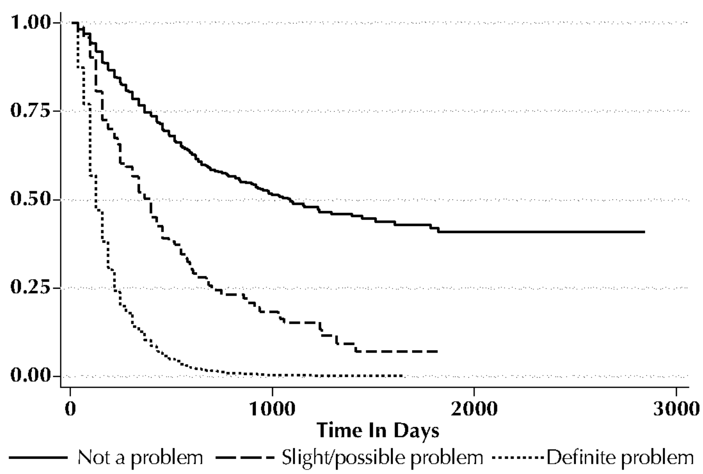

FIGURE 4.
Survival Curves by DRAOR Acute Negative Mood Rating