Daily Assessment of Acute Dynamic Risk in Paroled Offenders: Prediction, Predictive Accuracy and Intervention Effect

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Few studies have assessed acute dynamic risk repeatedly among paroled offenders to investigate the relationship between changes in acute dynamic risk and recidivism in crime. The present study investigates whether one-month changes in ten stress-related acute dynamic risk factors, collected through automated telephony while the participants were still in prison and over 30 consecutive days following parole, predict one-year criminal recidivism, including its predictive accuracy. The study also investigates whether a brief feedback intervention in conjunction with the daily assessments reduces recidivism compared to an assessment-only control group. Changes in five risk factors were found to be associated with increased risk of criminal recidivism after controlling for the results in prison, the initial value after parole, and the intervention. The predictive accuracy is marginally accurate: Summary score (AUC) = .666; Level of stress (AHSS) = .644; Psychiatric symptoms (SCL-8D) = .641; Anxiety symptoms = .673; Severity of most stressful daily event = .690. No differences in one-year recidivism rates were established between the intervention group and the control group. The study shows that daily assessments can usefully be made of dynamic risk factors in paroled offenders.

Key words: acute dynamic risk; intervention; paroled offenders; prediction; predictive accuracy; randomised controlled trial; recidivism.

Introduction

Criminal recidivism is a significant problem in relation to those who have served a prison sentence and are about to re-enter society. In Sweden, the highest rates of recidivism are found in paroled offenders, where one in five commit a new crime within the first year (Swedish National Audit Office, 2004).¹ It has been suggested that offenders' experiences in the immediate period following parole are of special importance and may be related to both the short- and long-term course of success or failure in the community (Nelson, Deess, & Allen, 1999, Zamble & Quinsey 1997). It is a period marked by potentially

high levels of stress, where released prisoners have to cope with a number of challenges (Bereswill, 2004; Seal, Eldridge, Kacanek, Binson, & MacGowan, 2007).

From a stress theoretical perspective, it could be argued that many of the challenges during transition to society are stressors, and that these may result in a physiological and emotional stress response. This stress response could either be an anxious response with autonomic arousal or a depressive response with reduced physical activity (Gelder, Harrison, & Cowen, 2006). The response experienced during stress may be managed through adaptive or maladaptive

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coping strategies, including substance use and recidivism in crime (Agnew, 1992; Brown, St Amand, & Zamble, 2009; Davis & Brantley, 2004; Zamble & Quinsey, 1997).

The identification and modification of risk factors in the critical period following release may be crucial in helping paroled prisoners during the reintegration process and reducing rates of criminal recidivism. Risk factors for criminal recidivism have been conceptualised as ranging from completely static and unchangeable factors (e.g. past criminal records and age of first offence) through stable dynamic factors (e.g. substance use disorders and high impulsivity traits that change over a long period) to acute dynamic factors (e.g. stress and current substance use that can change rapidly over a period of weeks, days or minutes; Hansson & Harris, 2000). Static risk factors are regarded as important for identifying absolute or relative risks but have limited implications for treatment since they are not changeable (Otto, 2000). In contrast, dynamic risk factors are crucial in treatment planning because, when they are subject to change, the reoffending rates will also change (Andrews & Bonta, 2010).

The predictive ability of static risk factors is well established and there is a growing body of evidence for the validity of dynamic factors in the prediction of future recidivism (for a review, see Serin, Lloyd, Helmus, Derksen, & Luong, 2013). However, most dynamic prediction studies have emphasised stable risk factors and have been criticised for being of limited use for making inferences about rapid changes in risk that enable effective daily management of offenders under community supervision (Serin, Chadwick, & Lloyd, 2015).

To increase the probability of detecting change, especially for dynamic variables that are expected to change rapidly, it has been suggested that researchers should employ multipoint studies with a prospective design involving at least three waves of assessments (Brown et al., 2009). With three or more occasions of measurement, more accurate –

as well as more complex – estimations of change can be modelled (Whiteman & Mroczek, 2007).

Prospective multipoint studies on the relationship between changes in acute risk factors and criminal recidivism have been performed among different populations in prison and probation services, including sexual offenders with community supervision (Hanson, Harris, Scott, & Helmus, 2007), general offenders on parole (Handby, 2013), and individuals on community supervision (Brown et al., 2009; Jones, Brown, & Zamble, 2010). However, the research is limited and attempts to identify significant acute dynamic factors have produced inconsistent results. In studies where predictive accuracy has been analysed, low to marginal/moderate accuracy is reported, where the strongest prediction models usually include dynamic as well as static risk factors (Brown et al., 2009; Handby, 2013; Hanson et al., 2007; Jones et al., 2010).

Limitations with Reference to Previous Studies

A major limitation, which concerns all the above studies, relates to the assessment of the acute dynamic risk factors studied, which are either assessed irregularly – where the time gap between the assessment varies between one week and several months (Handby, 2013; Hanson et al., 2007) – or with regular but infrequent intervals, e.g. 1, 3 and 6 months after release (Jones et al., 2010). The infrequent assessment of risk factors that are supposed to change rapidly makes continuous risk management difficult. The longer the interval between the assessments, the greater the risk that changes will be missed; assessments that fail to estimate the rate of change will miss increases and decreases in the risk state, including those associated with intervention (Douglas & Skeem, 2005).

Another limitation concerns how the relationship between acute dynamic risk factors and recidivism in crime has been analysed. A

common way to analyse this relationship in multipoint studies is to determine whether significant change has occurred over time. The assessment information closest to recidivism is then used to determine whether the reassessment of a dynamic variable is more predictable of recidivism than the previous – or a single – baseline assessment (Brown et al., 2009; Handby, 2013; Hanson et al., 2007; Jones et al., 2010). Such an approach discards important information by not considering that changes in dynamic risk scores may not only differ between individuals but also that risk scores may change over time for the same individuals.

There are several tentative explanations for the lack of studies systematically conducting intensive measurements that could capture the rapid changes that may occur in acute dynamic risk factors for released prisoners, as well as how these rapid changes could be related to criminal recidivism.

One important reason could be administrative. Most of the studies use extensive pen-and-pencil self-report questionnaires or structured professional judgements (SJPs), such as the Dynamic Risk Assessment of Offender Re-entry (DRAOR; Serin, 2007) or ACUTE-2007 (Hanson et al., 2007), which are usually administered by trained research assistants or by officers/practitioners working at the institution. Assessments of this kind are not feasible in the offenders' natural context and would make intensive assessments time-consuming and costly. The administrative burden placed on those collecting the data also has implications for the prison and probation services, where limited resources make it difficult to implement the use of constantly changing variables as well as extensive measures (Petersilia, 2003).

A second important reason may be related to the analytical challenges associated with linking analysis of change in dynamic risk scores with prediction analysis of recidivism in crime. A commonly applied modern approach to analysing change data is through growth modelling, a type of mixed-effects

model that allows the examination of the trajectories of individuals and groups in repeated-measures data (Whiteman & Mroczek, 2007). However, in many studies, the dynamic risk factors are measured at multiple points in time, while the outcome variable – recidivism in crime – is collected at one future point in time (Brown et al., 2009; Handby, 2013; Hanson et al., 2007; Jones et al., 2010). Standard longitudinal methods such as mixed-effects models, are designed for longitudinal outcomes and are therefore not directly applicable in this context.

Current Study

The present study attempts to overcome both the administrative and analytical obstacles described above by examining the relationship between daily changes in acute dynamic risk factors and its predictive accuracy for determining criminal recidivism.

The methodological obstacle is resolved by using data presented in a study by Andersson, Vasiljevic, Höglund, Öjehagen, and Berglund (2014), where interactive voice response (IVR) – an automated telephone system – was used to assess and intervene on the development of acute stress-related dynamic risk factors during the 30 days following parole in 108 Swedish offenders. To the authors' knowledge, the study conducted by Andersson et al. is the first to assess and intervene on the development of daily stress-related variables among prisoners on parole.

IVR is a well-established methodology for collecting self-reported data that has several advantages over similar techniques, such as text messaging and smartphone applications. IVR calls are natural reminders, increasing the probability of response. Collected data are immediately secured on the server and can be used for analysis and action. No information is stored on the handheld device when using IVR, which is especially important when handling sensitive information such as details of individuals' mental health and substance use.

The study conducted by Andersson et al. (2014) was a randomised controlled trial, where individuals in the intervention group received immediate feedback and recommendations based on a simple calculation of the direction of movement between the total score from the previous assessment compared with the total score on the current assessment. Brief cognitive interventions of this kind have been successfully used to help increase risk awareness in individuals with substance abuse problems and assist these individuals in thinking differently about problematic behaviour (Hendershot, Witkiewitz, George, & Marlatt, 2011). The fully automated system also sent a daily report by email to the probation officer, who could therefore monitor and intervene in regard to the dynamic risk factors. Several dynamic risk factors developed significantly more positively in the intervention group than in the control group. However, Andersson et al. did not assess the effect of the changes in daily variables on the actual rates of criminal recidivism, or whether there was an intervention effect on criminal recidivism.

In the present study, the second statistical obstacle is overcome by using a two-step analytic procedure. In the first step, a growth-curve model based on a linear mixed model is estimated for investigating the overall pattern of change in acute dynamic risk factors, i.e. trajectories or slopes. In the second step, the estimated subject-specific growth model trajectories – i.e. slopes – are used as predictors of recidivism in crime in a subsequent analysis. Maruyama, Takahashi, and Takeuchi (2009) describe such models in the context of a smoking cessation trial and, more recently, Mohr et al. (2013) used daily mood–drinking slopes to predict longer-term drinking motivation and alcohol problems.

The first aim of the present study is to investigate whether one-month changes in acute dynamic risk factors collected by automated telephony can predict recidivism in crime during the first year following parole. The second aim is to evaluate the predictive

accuracy of the one-month assessments in relation to one-year criminal recidivism. The third and final aim is to evaluate whether a brief feedback intervention in conjunction with the daily automated telephone assessments of acute dynamic risk factors reduces recidivism rates in comparison to an assessment-only control group.

Method²

Study Design

This study is an analysis of data from a randomised controlled trial, including daily data on the first-month course following parole and data on one-year criminal recidivism. A comprehensive description of the original study is presented in Andersson et al. (2014). The original study was designed to evaluate whether automated telephony could be used to perform daily assessments of acute dynamic risk factors in paroled offenders during their first 30 days after leaving prison. All participants were called daily and answered assessment questions. Based on the content of their daily assessments, the participants in the intervention group received immediate feedback and a recommendation by automated telephony, and their probation officers received a daily report by email. The present study was approved by the Regional Ethics Committee at Lund University (file number 2009-1) and registered at ClinicalTrials.gov (NCT01727882).

Procedure

Appointed employees at 13 out of 15 open and closed prisons in the south and east administrative regions of Sweden were assigned to identify all prisoners scheduled to leave prison on probation between December 2009 and August 2010. All participants were assigned a probation officer, had access to a mobile phone, and are sufficiently fluent in Swedish. Before probation, eligible participants were scheduled for a meeting with the

research group. Participants were told that registry data on criminal recidivism during one year following probation would be collected from the Prison and Probation Service, that participants could withdraw consent at any time, and that such withdrawal would result in their assessments being excluded. After written informed consent was obtained, the participants registered their probation date and mobile phone number into the automated telephone system, and responded to a baseline assessment including the same measurements that were later used during the follow-up period.

At registration, the participants were randomised into two groups. The automated telephone system was then programmed to call all participants, starting the day after probation – Day 1 – and continuing with daily assessments for 30 consecutive days. Attempts were made to reach participants every two hours between 12 p.m. and 9 p.m. during the follow-up period, i.e. Days 1 to 30. If contact was established, the automated telephone system collected follow-up data from the participant, and those randomised into the intervention group were given a brief feedback intervention that included recommendations, after which the call ended. After each assessment, the automated telephone system emailed a brief report to the assigned probation officer for those in the intervention group. When all daily data had been collected, in 2014, information about criminal recidivism was collected from the Swedish Prison and Probation Service's offender database.

Sample

As previously reported by Andersson et al. (2014), 108 paroled offenders took part in the original study; of these, 52 participants were originally randomised into an intervention group and 56 were in a control group. In this study, a total of 15 participants were excluded from the original sample: 7 from the intervention group and 8 from the control group. Of

these, 2 participants (1 from each group) were excluded because no follow-up data on criminal recidivism could be collected due to the death of the participant in one case and a missing personal identification number in the other. The remaining 13 participants (6 from the intervention group and 7 from the control group) were excluded because they responded to less than four of the follow-ups, so individual slope parameters could not be estimated.³ The final sample in the present study involves 93 paroled offenders: 45 from the original intervention group and 48 from the control group.

Measures

Both the baseline assessment and the 30-day assessment of acute dynamic risk factors, assessed through automated telephony, include 7 measurements and a total of 21 items. The participants gave a numeric response for 20 of these items simply by pressing a key on the telephone keypad, while the final question was an open-ended question where the respondent gave an oral response that was recorded.

Stress was measured with the 7-item Arnetz and Hasson Stress Scale (AHSS; Andersson, Johnsson, Berglund, & Öjehagen, 2009). A brief version of the Hopkins Symptom Checklist (SCL-8D; Fink et al., 1995) was used to assess psychiatric symptoms; subscales assessed symptoms of anxiety and depression. Two items from the Alcohol Urges Questionnaire (Bohn, Krahn, & Staehler, 1995) were used to assess cravings or urges to partake in alcohol and drugs, and the daily use of alcohol and drugs was assessed by simply asking the respondent to rate the intensity of use. Finally, assessment of daily experience (Stone & Neale, 1982) was used; participants were asked to orally record their most stressful event that day, where the severity of this event was rated on a numeric scale.

The present study only includes questions with a numeric response. For all numeric questions, responses were given on a 10-digit

scale ranging from 0 (negative) to 9 (positive). The ratings were reversed, meaning that a high score was considered less favourable and that improvements should result in lower scores.

The analysis includes ten different variables representing the following acute dynamic risk factors: stress, psychiatric symptoms, symptoms of depression, symptoms of anxiety, urge to drink alcohol, urge to use drugs, alcohol use, drug use, and the severity of the most stressful daily event. All of these variables, except the rating of most stressful daily event, were summarised to a total feedback score for 19 items, ranging from 0 (maximum positive) to 171 (maximum negative), which represents the final variable in the analysis. The Cronbach's alpha coefficient for the total scale over 31 assessments – i.e. including the baseline assessment and 30-day follow-up assessment – ranges between .89 and .98.

Finally, criminal recidivism is a dichotomous outcome variable (0 = no recidivism, 1 = recidivism) that is measured by criminal acts that resulted in a return to the criminal justice system, probation or prison during the one-year period following the prisoner's release.

Statistical Analysis

SPSS v23 was used in all statistical analyses (IBM Corp., Armonk, N.Y., USA). The baseline characteristics of the participants who were included and excluded from the final sample were compared using *t*-tests for means and chi-squared tests for proportions. A chi-squared test was also used to analyse the differences in one-year recidivism between the intervention group and the control group.

A two-step procedure was used to analyse whether one-month changes in acute dynamic risk factors collected by automated telephony can predict recidivism in crime during the first year following parole.

In the first step, growth modelling using a mixed-model procedure – which includes treatment of missing data – was used to assess

whether participants showed linear changes in acute dynamic risk factors during the first month following parole. Growth modelling is a type of multilevel modelling for repeated-measures data where the measurement occasions are nested within cases, i.e. individuals or participants. In the present analysis, level-1 units comprise the repeated measurements of acute risk factor for each participant, which describes how each participant changes over time, and level-2 units comprise the participants, and describes how changes in acute risk factors differ across participants. The intercept represents the initial starting point when the time equals zero and the slope indicates the rate of change from Day 1 over time. The time variable ranges from Day 1 to Day 30, where Day 1 represents the value of the acute risk factors studied the first day after parole. All models are controlled for the baseline values – i.e. assessments made in prison – of the acute risk factors, and the variances of the intercept and slope for each acute risk factor were also obtained, i.e. random effects. When using intercepts and slopes as predictors, significant variances – but not necessarily significant means – are required (Hampson, Tidesley, Andrews, Luyckx, & Mroczek, 2010).

In the second step, individual intercepts and slopes were extracted from the linear growth models, which enabled the modelling of growth-model slopes as predictors of recidivism in crime.

In clinical trials, when the outcome variable is dichotomous and the outcome prevalence is high (>10%), a modified Poisson regression with robust standard errors is thought to be a more suitable alternative than logistic regression, if the effects estimate of interest is risk ratio (Knol, Le Cessie, Algra, Vandenbroucke, & Groenwold, 2012). Logistic regression always overestimates the risk ratio if the outcome prevalence is high, and this overestimation becomes larger with increasing incidence of the outcome (Zhang & Yu, 1998).

Each slope was modelled separately in a Poisson regression analysis with robust standard errors, controlling for the growth model

intercept and the baseline value for each acute risk factor. The intervention was also included as a control variable. This resulted in ten different regression analyses – one for each acute dynamic risk factor. All variables were entered simultaneously into the model. Estimated risk ratios (RRs) with 95% confidence intervals (CIs) were used as a measure of the relative impact of the independent variables on criminal recidivism, where $RR < 1$ indicates an inverse association, $RR = 1$ indicates no association, and $RR > 1$ indicates a positive association.

Finally, to evaluate the predictive accuracy of the one-month assessments in relation to one-year criminal recidivism, predictive probabilities were calculated for those models that had a significant growth model slope from the Poisson regression analysis. The predictive values were used to analyse predictive accuracy for the different models by calculating the area under the receiver operator characteristic (AU-ROC).

The area under the curve (AUC) reflects the ability of the different models to discriminate between recidivism and non-recidivism. The curve is created by plotting the true positive rate (sensitivity) against the false positive rate (specificity) at various threshold settings. A result of 0.50 means no discriminatory ability, and 1.0 means perfect discriminative ability. Sjöstedt and Grann (2002) propose the following classification values for recidivism risk assessments: $< .60$ low accuracy; $.60-.69$ marginal accuracy; $.70-.79$ modest accuracy; $.80-.89$ moderate accuracy; $.90$ and above high accuracy. The average AUC value for commonly-used assessment tools – both static and dynamic – usually falls in the range of $.65$ to $.75$ (Daffern, 2007).

Results

Descriptive Analysis and Response Rates

Of the final sample of 93 participants, 43 committed a new crime that resulted in a return to the criminal justice system during the first year following parole. No differences

were found in the recidivism rates between those included in the final analysis and the 13 participants that were excluded due to limited response rates (46.2% vs 53.8%, $p = .800$).

In the final sample, baseline ratings for the most stressful daily event (3.23 ± 3.37) and drug use (0.58 ± 2.11) were less favourable than the corresponding ratings for those 13 participants excluded because of limited follow-up assessments (1.38 ± 1.76 , $p = .005$ and 0.00 ± 0.00 , $p = .009$, respectively). This difference remains significant even after adjusting for the 2 participants excluded because no follow-up data on criminal recidivism could be collected.

The final sample of 93 participants were able to respond to 30 daily follow-up assessments, resulting in 2880 possible assessments, and 2239 (77.7%) were completed. On average, participants completed 24.1 follow-up assessments ($SD = 8.0$, range = $4.0-30.0$). In the group excluded due to limited response rates ($n = 13$), the mean value of the response was 2 ($SD = 0.816$, range = $1.0-3.0$), while the two participants excluded due to missing data completed 8 and 25 assessments, respectively. Those in the final sample who committed a new crime during the first year following parole responded to fewer daily follow-up assessments during the first month compared to those who did not commit a crime (22.23 ± 8.42 vs 25.66 ± 7.28 , $p = .038$).

Analysis of Linear Change in Acute Risk Factors

The linear growth model parameters – i.e. the baseline values, intercepts and slopes for the acute dynamic variables in the total group of paroled offenders – are presented in Table 1.

The baseline values are significant for all acute risk factors except drug use, alcohol use, urge to drink alcohol, and ratings of the most stressful daily event, while the intercepts are significant for all the acute risk factors.

Table 1. Analysis of ten acute dynamic risk factors in the total group of paroled offenders ($n = 93$).

Variables	Analysis of linear change Estimate (<i>SE</i>)	Analysis of recidivism Risk ratio (95% CI)
Summary score		
Baseline	0.41 (0.10) ^{***}	1.000 (0.994–1.005)
Intercept	18.04 (6.12) ^{***}	1.008 (1.002–1.013) ^{**}
Slope	–0.06 (0.14)	1.087 (1.007–1.174) [*]
Intervention		1.371 (0.887–2.117)
Variance component:		
Intercept	888.64 (142.04) ^{***}	
Slope	1.43 (0.28) ^{***}	
AHSS – Stress		
Baseline	0.42 (0.10) ^{***}	1.001 (0.984–1.018)
Intercept	6.74 (2.54) ^{***}	1.016 (0.999–1.033)
Slope	–0.03 (0.05)	1.270 (1.031–1.565) [*]
Intervention		1.369 (0.887–2.114)
Variance component:		
Intercept	123.87 (20.21) ^{***}	
Slope	0.20 (0.04) ^{***}	
SCL-8D – Psychiatric symptoms		
Baseline	0.34 (0.08) ^{***}	0.999 (0.988–1.010)
Intercept	8.94 (2.49) ^{***}	1.015 (1.001–1.028) [*]
Slope	0.002 (0.07)	1.212 (1.028–1.430) [*]
Intervention		1.372 (0.882–2.134)
Variance component:		
Intercept	200.87 (32.87) ^{***}	
Slope	0.35 (0.07) ^{***}	
Alcohol use		
Baseline	0.03 (0.08)	0.984 (0.895–1.082)
Intercept	1.65 (0.21) ^{***}	1.157 (1.079–1.240) ^{***}
Slope	–0.015 (0.007) [*]	2.313 (0.485–11.022)
Intervention		1.447 (0.940–2.228)
Variance component:		
Intercept	2.90 (0.52) ^{***}	
Slope	0.002 (0.0007) ^{***}	
Alcohol urge		
Baseline	0.03 (0.07)	1.021 (0.948–1.099)
Intercept	1.21 (0.22) ^{***}	1.093 (1.005–1.190) [*]
Slope	–0.007 (0.007)	0.991 (0.338–2.905)
Intervention		1.247 (0.804–1.935)
Variance component:		
Intercept	3.02 (0.52) ^{***}	
Slope	0.003 (0.0008) ^{***}	

(continued)

Table 1. (Continued)

Variables	Analysis of linear change Estimate (SE)	Analysis of recidivism Risk ratio (95% CI)
Drug use		
Baseline	−0.02 (0.10)	1.024 (0.948–1.105)
Intercept	1.09 (0.21)***	1.133 (1.073–1.196)***
Slope	0.004 (0.008)	2.463 (0.735–8.247)
Intervention		1.339 (0.863–2.077)
Variance component:		
Intercept	3.55 (0.60)***	
Slope	0.004 (0.0008)***	
Drug urge		
Baseline	0.28 (0.08)***	1.035 (0.962–1.113)
Intercept	0.90 (0.59)***	1.101 (1.028–1.179)**
Slope	−0.0003 (0.007)	0.852 (0.251–2.894)
Intervention		1.166 (0.767–1.773)
Variance component:		
Intercept	3.76 (0.62)***	
Slope	0.003 (0.0007)***	
Rating of most stressful daily event		
Baseline	0.05 (0.064)	1.073 (1.011–1.138)*
Intercept	2.40 (0.30)***	1.100 (0.980–1.235)
Slope	−0.03 (0.011)*	6.305 (1.314–30.247)*
Intervention		1.365 (0.870–2.143)
Variance component:		
Intercept	3.63 (0.64)***	
Slope	0.008 (0.002)***	

Note. * $p \leq .05$; ** $p \leq .01$; *** $p \leq .001$. AHSS = Arnetz and Hasson Stress Scale; SCL-8D = a brief version of the Hopkins Symptom Checklist. The first section presents analysis of linear change, here presented as linear growth model estimates, i.e. baseline score, intercepts and slopes. The second section presents analysis of recidivism in crime, here presented as risk ratios.

The mean linear rates of changes – i.e. the slopes – are only significant for alcohol use and ratings of the most stressful daily event, meaning that during the first month following parole there was an average daily decrease in these two variables.

Significant variance components in the linear growth curve parameters – i.e. intercepts and slope – were found for all acute risk factors studied, indicating that the individual growth patterns deviate from the average growth patterns, and that change is occurring, although in different directions.

Analysis of Recidivism in Crime

Intercepts and slopes extracted from the linear growth models were used as covariates to analyse their association with recidivism in crime, controlling for the intervention and baseline values of each acute risk factor. The estimates and risk ratios are presented in Table 1.

All intercepts except those for depression, the AHSS and ratings of the most stressful daily event have a positive association with recidivism in crime. The analysis resulted in five significant slopes, where the risk ratios

for recidivism in crime range from 6.305 (CI = 1.314–30.247) for the slope for ratings of the most stressful daily event to 1.087 (CI = 1.007–1.174) for the summarised score slope. In summary, participants with higher scores – i.e. worsening symptoms – on the five significant acute dynamic risk factors had a higher risk of recidivism.

Predictive Accuracy

For the five acute risk factors with a significant slope in the analysis of criminal recidivism, predictive probabilities of recidivism in crime were calculated as a function of the baseline value, the growth model intercept, the growth model slope, and the intervention.

The AU-ROC values for the five variables are presented in Table 2. The AUCs range from .641 (CI = .528–.754) in the SCL model to .690 (CI = .581–.800) for ratings of the most stressful daily event, meaning that the different models containing acute dynamic risk factors are marginally accurate.

Prediction of Criminality by Intervention during the First Month

When the group that was randomly assigned to receive a brief feedback intervention based on daily assessments during the first month following parole ($n = 45$) is compared with the assessment-only control group ($n = 48$),

no differences are found in the rates of one-year criminal recidivism (51.1% vs 47.7%, $p = .409$).

Discussion

Few studies have assessed acute dynamic risk repeatedly among prisoners on parole to investigate the relationship between changes in acute dynamic risk scores and recidivism in crime. To the authors’ knowledge, this is the first study to evaluate this relationship using a daily diary methodology.

This study supports the feasibility of using IVR to collect self-reported data on daily stress-related variables from paroled offenders. The results show that changes in several of the acute dynamic risk factors assessed by automated telephony during 30 consecutive days following parole significantly predict one-year recidivism, although the predictive ability is only marginally accurate.

The findings from the growth model analysis imply that stress-related symptoms can change rapidly in the critical time period following the commencement of parole and should be addressed regularly in order to enhance decision-making for good outcomes. Significant variance in the linear growth curve slopes, i.e. random effects, were found for all acute risk factors studied, which indicates that some prisoners may have a more

Table 2. Analysis of predictive accuracy.

Area under the curve	
Test result variable(s)	Area (95% CI)
Summary score	.666 (.554–.777)**
AHSS	.644 (.533–.757)*
SCL-8D	.641 (.528–.754)*
Anxiety	.673 (.565–.782)**
Rating of most stressful daily event	.690 (.581–.800)**

Note. * $p \leq .05$; ** $p \leq .01$. AHSS = Arnetz and Hasson Stress Scale; SCL-8D = a brief version of the Hopkins Symptom Checklist.
 AU-ROC values for the five acute risk factor models with a significant slope.

reactive response to specific stressors and more negative development as a result of stress-related symptoms during the 30-day follow-up.

The risk assessment literature does not provide any guidelines regarding optimal timelines for measuring change among different types of dynamic risk factors (Douglas & Skeem, 2005). However, related research indicates that daily fluctuations in stress-related variables are important for understanding different outcomes, and that difficult transitions can have a significant impact on these variables (Almeida & Wong, 2009; Gottfredson & Hussong, 2011; Mohr et al., 2013). This study adds to that body of research.

The acute dynamic risk factor showing the strongest risk with recidivism in crime was found to be severity of the most stressful daily event, followed by daily symptoms of anxiety and stress. Previous research suggests that acute dynamic factors may initially be environmentally based, which often stimulate a series of acute dynamic emotional responses, like stress and anxiety (Brown et al., 2009; Zamble & Quinsey, 1997). For example, Jones et al. (2010) and Brown et al. (2009) found that acute environmental triggers like job loss and marital discord, as well as acute emotional appraisals like negative affect, show empirical support with recidivism in crime. This study reports on the severity but not the type of most stressful event; the type of stressful event will be presented in a separate article.

No association was established between changes in the daily substance use variables and recidivism in crime. Substance use is considered to be a maladaptive coping strategy that is often used to reduce negative emotions like anxiety and stress (Agnew, 1992; Zamble & Quinsey, 1997). The role of substance use in predicting criminal recidivism has been established in earlier studies (Brown et al., 2009; Hakansson & Berglund, 2012; Hanson et al., 2007) and, in the Swedish prison system, around 66% of prisoners are

estimated to suffer from a substance abuse problem (Hakansson & Berglund, 2012). However, it cannot be excluded that some individuals may have denied or underreported the use of alcohol and drugs due to fear of negative consequences from their probation officer, even though confidentiality was assured.

The ability of the pattern of changes in acute risk factors to discriminate between recidivist and non-recidivist was marginally accurate. However, whether a specific AUC value is considered small or large depends on the context, and other more liberal classification values have been suggested in the context of recidivism risk assessments (Rice & Harris, 2005). The average AUC value for commonly-used risk assessment tools – static as well as dynamic – is usually in the range of .65 to .75 (Daffern, 2007). The AUC values obtained in this study fall approximately within that range and are similar to earlier findings on the predictive ability of acute dynamic variables (Handby, 2013; Hanson et al., 2007).

Compared to earlier studies, this study uses all repeated measurements on acute dynamic risk – rather than just the final measurement – as predictors of recidivism in crime. Using the full range of information on repeated measurements gives a more nuanced understanding than only analysing how conditions at last follow-up are related to recidivism. For example, some offenders may have negative development in stress-related symptoms while others remain constant. Their prognoses may appear similar if only one value is accounted for, but the offender with negative development may be at higher risk of recidivism. Whether a change score or a last score is a better predictor of recidivism in crime warrants further investigation.

The brief automated feedback intervention – based on the direction of movement between the total score from the previous assessment compared with the total score of the current assessment during 30 consecutive days of daily assessments – did not result in

reduced one-year criminal recidivism. The results presented by Andersson et al. (2014) show that this kind of intervention has a positive effect on stress-related acute dynamic risk factors over the assessment period. However, the effects of brief automated interventions are usually short term, and 12-month effects are rarely reported (Balhara & Verma, 2014). A recent review by Kouyoumdjian et al. (2015) shows only a few randomised controlled trials that have implemented effective interventions in the community after release from prison, one of which is the study by Andersson et al.

Adaptive coping strategies are important in altering negative consequences, and these are a major component in relapse prevention (RP) programmes (Hendershot et al., 2011). Such strategies have been shown to be effective in reducing both relapses in substance use (Dutra et al., 2008; Irvin, Bowers, Dunn, & Wang, 1999) and recidivism in crime (Dowden, Antonowicz, & Andrews, 2003). A frequently-used technique to deliver RP is brief interventions, which in their shortest form only include assessment followed by clear feedback (Hendershot et al., 2011).

Strengths and Limitations

Compared to earlier studies, the frequent assessment schedule implemented in this study provides more detailed data regarding the risk progression during parole and allows earlier detection of change in the critical time following parole. Using IVR to assess acute dynamic risk factors is a novel, low-cost approach that places a low burden of effort on the individuals responding to the instrument.

The present study also has several limitations. Firstly, no static or stable dynamic risk factors for criminal recidivism are included. Static as well as stable dynamic risk variables are acknowledged to predict criminal recidivism, and the best predictive model for criminal recidivism includes static, stable dynamic, and acute dynamic risk factors in

an overall assessment of risk (Brown et al., 2009; Hanson et al., 2007). Whether the acute risk factors used in this study led to incremental improvement in prediction accuracy above and beyond static and stable dynamic factors warrants further investigation.

Secondly, the participants included may differ from the general population of offenders since the sample was continuously recruited, so offenders who received shorter sentences may be somewhat overrepresented.

Thirdly, recidivism is treated as a binary outcome because the exact time of reoffending is not available for all participants in the study. A binary outcome is usually a downgrading from a time-to-event outcome, and is therefore less informative.

Fourthly, in the growth model analysis used here, no correlation structure is pre-specified. Specifying a correlation structure adds more parameters to be estimated and additional participants would be excluded because the number of parameters in the model would exceed the number of observations. In many daily diary studies, the repeated observations are assumed to be an exponentially decreasing function of time, which is specified by using a first-order autoregressive correlation structure (Bolger & Shrout, 2007).

Fifthly, recidivism is measured as the return to the criminal justice system, prison or probation. The further along the criminal justice system a data source about recidivism is, the more likely it is to underestimate the recidivism rate, since many crimes are not detected and reported, or do not result in charges being laid (Payne, 2007).

Conclusion

These findings add an important contribution to the current discussion on whether acute dynamic risk factors could be used to predict recidivism and monitor risk in parolees during their transition back into society (Ward, 2016). Automated techniques could be an innovative and important direction for future research within the field of risk assessments,

as well as for practitioners— working in the prison and probation services – who lack the resources to monitor and intervene on dynamic risk factors on a daily basis (Petersilia, 2003).

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Notes

1. Parole refers to the mandatory release and community supervision of a prisoner once two thirds of his prison sentence has been served.
2. This study follows consensus-based guidelines for what should be routinely reported in risk assessment research (Singh, Yang, Mulvey, & the RAGEE Group, 2015).
3. The number of parameters that a growth model can estimate is one less than the number of occasions ($n - 1$). In a linear model with one covariate there will be three estimates – one slope, one intercept, and the covariate – so at least four points in time are needed.

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