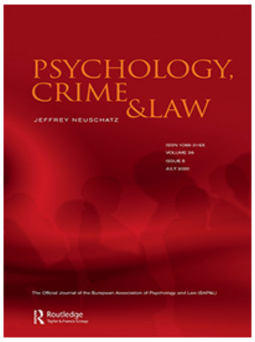

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Incremental validity of ambulatory assessment of acute dynamic risk in predicting time to recidivism among prisoners on parole

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ABSTRACT

This study investigates the incremental validity of changes in ten stress-related acute dynamic risk factors, collected through automated telephony over 30 consecutive days following parole, for predicting time to recidivism during the following year. Before release, the participants completed self-report assessment of some stable risk factors – impulsiveness and history of problematic substance use – as well as an assessment of symptoms of anxiety experienced during the weeks prior to release. Analysis of the baseline assessments showed that impulsiveness and a history of problematic substance use, but not pre-release symptoms of anxiety, were associated with recidivism during the parole year. Growth modelling using a linear mixed model was used to assess whether inmates on parole showed changes in acute dynamic risk factors during the first month following release. Individual growth model slopes and intercept were then extracted and used as covariates in a series of Cox regression analyses to test whether changes in acute dynamic risk factors could provide incremental predictive validity beyond baseline stable risk factors. Changes in five dynamic risk factors were associated with an increased risk of recidivism, of which daily drug use and daily summary score showed incremental predictive improvement beyond impulsiveness and history of problematic drug use.

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Acute dynamic risk; incremental validity; paroled offenders; recidivism; prediction

One of the main challenges in risk assessment is to develop valid and efficient tools for assisting probation officers in their day-to-day management of offenders on parole (Douglas & Skeem, 2005). The immediate time after release back into the community is often considered to be of special importance; recidivism rates are high, and offenders are faced with numerous challenges (Petersilia, 2003). With effective monitoring of relevant risk factors, the probation officers can make better judgments of when an individual is at risk, and decide how and when to intervene to reduce that risk (Douglas & Skeem, 2005).

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Recidivism risk assessments have undergone considerable evolution, from unstructured clinical expert assessments, via actuarial assessments based only on static risk factors like criminal history and age of first offence (Andrews, Bonta, & Hoge, 1990), to dynamic risk factors like insight and motivation (Webster, Douglas, Eaves, & Hart, 1997). Actuarial instruments are reliable and often demonstrate good predictive validity (e.g. Bonta & Yessine, 2005), particularly if the group subject to prediction is heterogeneous. However, the nature of the predictors does not permit measurement of changes in risk over time, so cannot be used to select and verify effects of risk-reducing interventions (Andrews & Bonta, 2010).

One major implication of the shift in focus from static to dynamic risk is that risk assessment should be conducted repeatedly to detect any potential changes over time (Douglas & Skeem, 2005). Correctional resources are limited, so reassessments must be easy for correctional staff, who typically have heavy workloads and often lack standardised training (Jones, Brown, & Zamble, 2010). Dynamic risk assessment may greatly influence correctional decision-making, so it is also crucial that the reliability and validity of the methods used are on acceptable levels. Clinicians must ensure that the methods selected to assess dynamic risk are capable of detecting change that has occurred, and are meaningful in that any change that has occurred is predictive of increases or decreases in recidivism risk (Andrews & Bonta, 2010). Incremental validation of dynamic reassessments is also vital, given the ease and speed with which reliable single point estimates of risk can be obtained (Brown, St. Amand, & Zamble, 2009).

Over recent decades, researchers have identified several dynamic risk factors (e.g. antisocial and impulsive personality traits, substance misuse) that can predict general recidivism as well as or even better than static risk factors (Gendreau, Little, & Goggin, 1996; Zamble & Quinsey, 1997; HCR-20^{V3}, Douglas, Hart, Webster, & Belfrage, 2013). Some risk instruments have a very short time frame (e.g. 24 h) and measure a highly specific set of purely dynamic factors (e.g. Brøset Violence Checklist, BVC; Almvik & Woods, 1999). However, most instruments used in prison or forensic psychiatric settings have a much longer time frame and include a combination of static and dynamic factors. Dynamic factors vary considerably in terms of time frame and the degree to which they can be changed by interventions. For instance, impulsiveness is a strongly hereditary trait, but the impact and severity of this trait can seemingly be reduced by proper interventions (Romer, 2010).

To date, most dynamic prediction studies have emphasised dynamic risk factors that are relatively stable over time (for a review, see Serin, Lloyd, Helmus, Derkzen, & Luong, 2013). Such factors, like psychopathy, antisocial and impulsive personality traits, and substance use problems, are expected to remain unchanged for long periods and are of limited use for making inferences about the daily management of offenders under community supervision (Serin, Chadwick, & Lloyd, 2015).

Acute dynamic risk

More recently, a new group of dynamic risk measures has been developed, aimed at assessing rapidly changes in risk that can inform case planning and risk management in real time or close to real time (Serin et al., 2015). Acute, rapidly changing factors, such as stress, negative mood or daily alcohol and drug use, can signal the imminence of re-offence, and are suggested to be particularly useful for monitoring risk during community supervision (Hansson & Harris, 2000).

To date, most change studies on dynamic risk are based on just two data points – often collected prior to, and then following, treatment (e.g. Olver & Wong, 2013). To increase the likelihood of detecting change, particularly for dynamic variables that are expected to change rapidly, it has been recommended that researchers should employ multi-point studies involving at least three waves of assessment (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).

Multi-point studies have been performed on the relationship between changes in acute risk factors and criminal recidivism 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 et al., 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). In addition, all these studies have notable methodological and statistical weaknesses, namely, infrequent assessments of variables that are supposed to change rapidly, and utilising only a small fraction of the available dynamic risk information in the prediction analysis of crime (Vasiljevic, Berglund, Öjehagen, Höglund, & Andersson, 2017). Even if dynamic risk factors are measured repeatedly over time, risk scores are typically based on the last available measurement.

Methodological challenges in measuring acute dynamic risk

Collecting data for rapidly changing risk factors is clinically and statistically challenging. The participants need to be tracked in the community and assessed intensively over time. Despite advances in technology in recent decades, risk assessment, as typically practiced, still relies on Structured Professional Judgments (SPJ), actuarial assessments, and/or traditional paper-and-pencil questionnaires. Assessments of this kind are limited in various ways – for example, intensive assessment of constantly changing variables would be time-consuming and costly.

Linking analyses of change in dynamic risk scores with prediction analysis of recidivism in crime also poses some significant statistical challenges (Yang, Guo, Olver, Polaschek, & Wong, 2017). One is that dynamic risk factors are typically collected repeatedly over a shorter period, while the outcome variable – recidivism in crime – is collected at one future point in time. Standard longitudinal methods, such as the mixed effects model, are designed for longitudinal outcomes so are not directly applicable in this context.

Ambulatory assessment

Ambulatory assessment (AA) covers a wide range of assessment methods, increasingly computerised, to study people in their natural environment in real time or near real time (Trull & Ebner-Priemer, 2013). The 'real time' aspect of AA enables researchers and clinicians to understand and monitor experiences as they occur, which is especially important for experiences that are transitory and often misremembered (e.g. anxiety, stress and daily substance use).

Interactive Voice Response (IVR) is a well-established methodology for collecting self-reported ambulatory data that has several advantages over similar techniques, such as text messaging and smart-phone applications. IVR calls are natural reminders, increasing the probability of response. Collected data is kept secure on the server and can be used for immediate analysis and action, or batch analyses. No information is stored on the hand-held device when using IVR, which is especially important when handling sensitive information, such as individuals' psychiatric symptoms and substance use.

To our knowledge, only two studies have applied an AA approach to assess rapidly changing risk factors among released prisoners (Andersson, Vasiljevic, Höglund, Öjehagen, & Berglund, 2014; Vasiljevic et al., 2017), both conducted on the same sample used in the present study.

The original study, a randomised controlled trial, conducted by Andersson et al. (2014), investigated whether IVR can be used to assess and intervene on the development of everyday stress-related risk factors during the 30 days following parole in 108 Swedish offenders. The intervention included a brief computerised feedback based on assessment responses, aimed to reduce peak symptoms in daily stress related variables. The feedback to the paroled offender was given immediately after each assessment, based on a calculation of the direction of movement between the total score from the previous daily assessment compared with the total score on the current daily assessment. In cases where the calculation indicated a negative trend, a recommendation was given to the respondent to talk to someone trusted, for example, the probation officer. The intervention also included a daily report sent by email to the probation officer, intended to improve decisions on individual need of care.

By using a linear growth-model approach, the study by Andersson et al. (2014) found that the intervention group ($n = 52$) had a significantly better improvement, i.e. a positive change, than those in the control group ($n = 56$) for several measures of stress-related acute dynamic risk factors over the assessment period. In total scores, the intervention group improved, on average, by 9.6 points more over the assessment period as compared to those assigned to the control group (CI = 0.5–18.7, $p < .05$).[1]

In a follow-up study on a reduced sample from the same group of offenders ($n = 93$), Vasiljevic et al. (2017) examined whether changes in everyday stress-related variables were predictive of one-year criminal recidivism. The study also investigated whether the brief feedback intervention reduced recidivism, and no differences were found between the intervention and control group (51.1% vs 47.7%). To alleviate the statistical shortcomings from previous studies on acute risk factors, Vasiljevic et al. (2017) used a two-stage approach. In the first step, a growth model was estimated based on the longitudinal data. In the second step, the estimated values of the longitudinal trajectories were entered as predictors of recidivism in crime. Yang et al. (2017) have previously described such models in the context of dynamic risk assessment.

Although Vasiljevic et al. (2017) found that daily changes in five of the ten acute risk factors measured were marginally predictive of one-year criminal recidivism (AUC range 0.64–0.69), the study did not examine whether the acute risk factors lead to incremental predictive improvements when added to more recognised risk factors. If a measure cannot make better predictions than those achieved by more established risk factors, then its predictive efficiency is brought into question (Conroy & Murrie, 2007).

Current study

The current study addresses the limitations from Vasiljevic et al. (2017) as well as previous multipoint studies addressing acute dynamic risk by examining the incremental validity of IVR-based ambulatory assessments in predicting time to recidivism among Swedish prisoners on parole.

Consistent with the previously presented studies (Andersson et al., 2014; Vasiljevic et al., 2017), this study uses a stress-theoretical framework to understand how challenges in the period immediately following parole may be related to criminal recidivism. From a stress theoretical perspective, it could be argued that many of the challenges during transition to society are stressors, which may result in an anxious or depressive stress response. The response experienced during stress may be managed through adaptive or maladaptive coping strategies, where the latter includes substance use and recidivism in crime (Agnew, 1992; Brown et al., 2009; Zamble & Quinsey, 1997).

However, how offenders respond to a certain situation may also be affected by more stable propensities to react in a maladaptive manner, like impulsive personality traits, substance use problems or mental health problems (Zamble & Quinsey, 1997). Previous analysis of the baseline data, i.e. assessment in prison, on the same sample used in the present study suggests that self-reported impulsiveness, a history of problematic drug use, and symptoms of anxiety experienced in prison during the weeks prior to release, are weakly or moderately predictive of recidivism during the year following release (AUC range 0.61–0.64) (Vasiljevic, Öjehagen, & Andersson, 2017).

The aim of the current study is to investigate whether changes in stress-related acute risk factors, collected through automated telephony over 30 consecutive days following parole, provide incremental predictive ability beyond the baseline assessment of stable risk factors in predicting time to criminal recidivism during the year after release from prison.

Method[2]

Procedure

Appointed employees at 13 out of 15 minimum-, medium-, and maximum-security prisons in the South and East administrative regions of Sweden were assigned to identify all prisoners about to leave prison on probation between December 2009 and August 2010. All participants should have been assigned a probation officer, have access to a mobile telephone, and be 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 over 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 informed consent, participants registered probation date and mobile phone number into the automated telephone system, and responded to a baseline assessment that included assessment of personality, substance use, mental health, and the same daily 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 noon and 9 pm during the follow-up period, i.e. Days 1–30. 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 based on the content of their daily assessments, 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 offender database.

The present study was approved by the Regional Ethics Committee at Lund University (file number 2009-1), and was registered at ClinicalTrials.gov (NCT01727882).

Sample

The original study involved 108 paroled offenders; of these, 52 subjects had originally been randomised into an intervention group and 56 were controls (Andersson et al., 2014). In the current study, a total of 18 subjects were excluded from the original sample, nine from the intervention group and nine from the control group. One intervention subject was excluded because he died during the follow-up year, and one control subject was excluded because he had no social security number and could not be traced in the crime register. Sixteen subjects were excluded because they had too few valid follow-ups for the regression analysis to be performed (less than four).[3] Three of the 16 excluded subjects reoffended within the first three days following parole.[4] The final sample in the present study involved 90 paroled offenders, 43 from the original intervention group and 47 from the control group.

Measures

Acute risk factors

The acute risk factors, assessed through automated telephony, consisted of a baseline assessment and the 30-day assessment of everyday stress-related risk factors. The assessment included seven measurements, and a total of 21 items. A numeric response was given to 20 of these items, simply by pressing a key on the telephone keypad, while the final question was an open-ended question to which the respondent gave an oral response that was recorded.

Stress was measured with the seven-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 symptoms of anxiety and depression. Two items from the Alcohol Urges Questionnaire (Bohn, Krahn, & Staehler, 1995) were used to assess craving for alcohol and drugs, respectively. 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 ten-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 daily acute dynamic risk factors: stress, mental health symptoms sum score, subscore symptoms of depression and anxiety, urge for alcohol, urge for drugs, alcohol use, drug use, and severity of the most stressful daily event. All these variables, except 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), and which represents the tenth and final variable in the analysis.

Stable risk factors

Impulsivity was measured with the Impulsiveness scale from the Karolinska Scales of Personality (Schalling, 1978). The Impulsiveness scale consists of ten items measuring acting on the spur of the moment, non-planning, preference for speed rather than accuracy, and care-freeness on a 4-point Likert scale.

Drug use problems were assessed using the Drug Use Disorders Identification Test (DUDIT) (Berman, Bergman, Palmstierna, & Schlyter, 2005), a self-report scale with eleven items and a total score range of 0–44. Drug-related problems are identified at a cut-off score of ≥2 for women and ≥6 for men.

Pre-release symptoms of anxiety were assessed using ten relevant items of the Hopkins Symptom Checklist 25 (HSCL-25) (Nettelbladt, Hansson, Stefansson, Borgquist, & Nordström, 1993). Symptoms are assessed over the previous two weeks. The responses are summarised across all items and the mean score makes up the total score, which ranges from 1 to 4.

Criminal recidivism

The *Time at risk* variable was defined as days from release from prison until the first criminal act that resulted in a return to the criminal justice system or until data was censored at the end of the study, 364 days following parole.

Statistical analysis

Baseline characteristics of subjects who were included and excluded from the final sample were compared using t-test for means, and chi-2 test for proportions. Some offenders (under 10%) did not complete the KSP-impulsiveness questionnaire. To reduce bias from selective data loss, missing data was imputed with group mean values (recidivist/non-recidivist).

For the primary analysis examining recidivism in crime, analyses were conducted in two stages. In the first stage, growth modelling using a linear mixed model was used to assess whether inmates on parole showed linear changes in acute dynamic risk factors during the first month following parole. The growth model intercept represents the initial starting point when time equals zero and the slope indicates the rate of change from Day 1 over time. The time variable ranged 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 were 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. Using intercepts and slopes as predictors requires significant variances but not necessarily significant means (Hampson, Tideseley, Andrews, Luyckx, & Mroczek, 2010). Significant variances indicate that changes in acute risk differ across participants.

In the second stage, individual intercepts and slopes for the ten acute variables were extracted from the linear growth models and used as covariates in a hierarchical Cox regression analysis to test whether changes in acute dynamic risk factors had any incremental predictive validity beyond the baseline measures of stable dynamic risk. Each slope was modelled in a separate hierarchical regression, controlling for stable dynamic risk factors. The growth model intercept and the intervention were also included as control variables. This resulted in ten different regression analyses, one for each acute dynamic risk factor. All continues variables were standardised prior to the main statistical analysis, i.e. Cox regression analysis. Tests of the incremental value were based on Likelihood Ratio estimates.

Results

Descriptive analysis and response rates

Of the final sample of 90 subjects, 40 committed a new crime resulting in a return to the criminal justice system during the first year following parole (19 from the control group, and 21 from the intervention group). Of the 40 subjects that committed a new crime, 6 reoffended prior to the end of the 30-day follow-up period. The mean time of failure was 138 days for those who reoffended during the first year following parole. Mean age of the final sample was 36.7 (SD = 10.8), with no age differences between the recidivist and non-recidivist group.

There were no differences in recidivism rates between those included in the final analysis and the 18 subjects that were excluded (44% vs. 63%, $p > 0.10$). Comparison of baseline ratings on stable and acute risk factors between the final sample of 90 subjects and the 18 excluded subjects yielded no significant differences.

The final sample of 90 subjects could respond to 30 daily follow-up assessments, resulting in 2700 possible assessments, and 2183 (81%) were complete. On average, subjects completed 24.3 (SD 7.9; range 4–30) follow-up assessments. Twenty-eight (31.1%) of the subjects participated in all the follow-up interviews, 66 (73.3%) participated in at least 3 quarters of the follow-ups, and a total of 75 (83.3%) completed at least half of the telephone follow-ups. The remaining 15 subjects completed on average 8.1 (SD = 2.6) follow-ups. 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 those who did not commit a crime (22.5 ± 8.31 vs. 25.7 ± 7.28, $p < .05$).[5]

Differences in mean values between recidivist and non-recidivist in acute dynamic risk over the assessment period are presented in Table 1. The recidivist showed significant higher mean values compared to non-recidivist on 7 out of 10 acute dynamic risk factors included in this study.

Table 1. Differences in mean values between recidivist ($n = 40$) and non-recidivist ($n = 50$) in acute dynamic risk over the assessment period (day 1–30).

Variables	Total ($n = 90$) M ± SD	Recidivist M ± SD	Non-recidivist M ± SD	Group comparison
Summary score	42.4 ± 32.0	50.1 ± 33.2	35.9 ± 29.7	<.05
AHSS – stress	0.8 ± 0.3	0.8 ± 0.3	0.7 ± 0.3	NS
SCL-8D – Mental health symptoms sum score	17.5 ± 15.6	20.8 ± 15.7	14.7 ± 15.1	NS
Depression subscale	4.7 ± 8.8	6.8 ± 8.7	2.9 ± 8.6	<.05
Anxiety subscale	9.0 ± 8.1	10.6 ± 8.2	7.6 ± 7.9	NS
Alcohol use	1.4 ± 1.7	1.9 ± 1.9	0.9 ± 1.4	<.01
Alcohol urge	1.2 ± 1.7	1.7 ± 1.9	0.8 ± 1.4	<.05
Drug use	1.1 ± 1.8	1.7 ± 2.1	0.6 ± 1.5	<.01
Drug urge	0.4 ± 0.4	0.5 ± 0.4	0.3 ± 0.3	<.001
Rating of most stressful everyday event	2.3 ± 1.9	2.8 ± 2.0	1.8 ± 1.7	<.01

Note: Comparison on ratings on acute risk factors between recidivist and non-recidivist were assessed by Mann-Whitney U tests.

Incremental validity of acute dynamic risk

Prior to conducting the main analysis, simple and multiple Cox regression analyses were performed on the relationship between baseline stable risk factors and recidivism in crime. The results are presented in Table 1. Impulsiveness, mean scores on drug use, and problematic drug use, but not anxiety, were significantly related to recidivism in crime.

Linear growth model parameters, i.e. baseline values, intercepts and slopes for the acute dynamic variables in the total group of paroled offenders, are presented in Table 3. The mean linear rates of changes – i.e. the slopes – are only significant for ratings of the most stressful daily event, meaning that during the first month following parole there was an average daily decrease by 0.03 units in this variable. Significant variance components in the linear growth curve parameters – i.e. intercepts and slopes – were found for all acute risk factors studied.

For the main analysis focusing on the incremental predictive validity of acute dynamic risk, baseline stable risk factors problematic drug use and impulsiveness were entered first. In a second block, intercepts and slopes extracted from the linear growth models were entered as covariates simultaneously, together with the intervention. The estimated hazard ratios for the final models are presented in Table 3. The analysis resulted in five significant slopes, of which the models containing summary score (χ^2 (3) = 8.61, $p < 0.04$), and

Table 2. Hazard ratios for baseline measures of impulsiveness, pre-release symptoms of anxiety (HSCL-25), problematic drug use (DUDIT), and recidivism in crime ($n = 90$).

Variable	HR	(CI)
Impulsiveness	1.563**	(1.132–2.158)
HSCL		
Anxiety sub-score	1.653	(0.945–2.892)
DUDIT		
Total score	1.015*	(1.002–1.028)
≥ 2/6	3.387**	(1.559–7.360)
Multiple regression		Model values
	HR	(CI)
Impulsiveness	1.407*	(1.021–1.938)
DUDIT ≥ 2/6	2.947**	(1.339–6.487)

**$P < 0.01$; *$P < 0.05$.

daily drug use (χ^2 (3) = 8.79, $p < 0.03$) showed incremental predictive improvements beyond the two stable dynamic risk factors, impulsiveness and problematic drug use.[6] For the model including daily alcohol use, the slope was not significant, while the model as a whole showed incremental predictive improvement beyond the stable risk factors (χ^2 (3) = 8.25, $p < 0.04$). Even if the slope is not significant, the model shows that the intercept, i.e. alcohol use in the first day following parole, has a relatively strong significant effect on recidivism in crime, after controlling for impulsiveness and problematic drug use (Table 3).

Discussion

The current study aimed to investigate whether changes in acute dynamic risk factors, collected through automated telephony, among prisoners on parole provide incremental predictive ability beyond the baseline assessment of some stable risk factors. Results showed that changes in summary score, and drug use, in the month following parole was found to add predictive power beyond self-reported measures of impulsiveness trait and history of problematic drug use.

For practical applicability in risk assessment, a measure or procedure should be able to predict above and beyond more commonly used measures known to predict the outcome in question. Two relatively common predictors in recidivism prediction are impulsivity and substance use problems (Andrews & Bonta, 2010). In this study, criminal recidivism was predicted by self-reported baseline measures of impulsiveness trait and history of problematic substance use. A previous study on the same sample had found mental health problems, i.e. symptoms of anxiety during weeks prior to release, to be predictive of criminal recidivism (Vasiljevic et al., 2017), but no such relationship was found in this study.

Mental health problems, as well as impulsiveness, and substance use problems, are variables that may moderate the effects of everyday stress on an offender's decision making as well as coping ability. For example, previous studies on acute dynamic risk among violent offenders have suggested that individuals with mental health problems are less capable of handling stressful situations and are at higher risk of committing violent crimes when under stress (Haggård-Grann, Hallqvist, Långström, & Möller, 2006).

The main results in this study imply that changes in prisoner's emotional state, and substance use behaviour, i.e. acute risk factors, in the month following release may significantly affect the ability of released prisoners to successfully reintegrate into the community. The probability for recidivism increased by 48% for each unit increase in the daily summary score (HR = 1.478), and by 52% (HR = 1.522) for each unit increase in daily drug use, after controlling for self-reported impulsiveness and history of problematic drug use.

These findings are consistent with previous studies, showing that stressors in the time following release, as well as the offender's coping ability, play a pivotal role in successful re-entry (Brown et al., 2009: Jones et al., 2010; Zamble & Quinsey, 1997). 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). Many offenders have weak coping skills, being unable to recognise and deal with problem situations, which may lead to increased stress levels, substance use and impulsive criminal reactions (Zamble & Quinsey, 1997).

Table 3. Analysis of ten acute dynamic risk factors in the total group of paroled offenders ($n = 90$).

Variables	Analysis of change Estimates (SE)	Analysis of recidivism Hazard ratio (95% CI)
Summary score		χ^2 (3) = 8.61, $p = 0.04$
Baseline	.40 (.11)***	
Intercept	18.86 (6.27)**	1.636 (1.155–2.138)**
Slope	−.05 (.14)	1.478 (1.021–2.141)*
Intervention		1.446 (0.714–2.738)
DUDIT ≥ 2/6		2.713 (1.227–5.997)*
Impulsiveness		1.290 (0.936–1.778)
Variance component		
Intercept	911.71 (148.09)***	
Slope	1.46 (.29)***	
AHSS – Stress		χ^2 (3) = 6.79, $p = 0.08$
Baseline	.41 (.10)***	
Intercept	7.17 (2.59)**	1.495 (1.051–2.126)*
Slope	−.03 (.06)	1.462 (0.995–2.147)
Intervention		1.420 (0.752–2.680)
DUDIT ≥ 2/6		2.784 (1.262–6.141)**
Impulsiveness		1.314 (0.956–1.806)
Variance component		
Intercept	125.71 (20.21)***	
Slope	.21 (.04)***	
SCL-8D – Mental health symptoms sum score		χ^2 (3) = 7.00, $p = 0.07$
Baseline	.33 (.08)***	
Intercept	9.25 (2.57)***	1.559 (1.083–2.245)*
Slope	.003 (.07)	1.513 (1.000–2.288)*
Intervention		1.434 (0.758–2.713)
DUDIT ≥ 2/6		2.935 (1.332–6.468)**
Impulsiveness		1.314 (0.955–1.809)
Variance component		
Intercept	207.90 (33.68)***	
Slope	.36 (.07)***	
Depression subscale		χ^2 (3) = 5.76, $p = 0.12$
Baseline	.30 (.09)**	
Intercept	4.99 (1.27)***	1.569 (1.052–2.339)*
Slope	.007 (0.04)	1.436 (0.955–2.158)
Intervention		1.393 (0.736–2.636)
DUDIT ≥ 2/6		2.952 (1.339–6.508)**
Impulsiveness		1.315 (0.955–1.810)
Variance component		
Intercept	52.14 (8.56)***	
Slope	.10 (.02)***	
Anxiety subscale		χ^2 (3) = 7.39, $p = 0.06$
Baseline	.32 (.08)***	
Intercept	4.81 (1.26)***	1.531 (1.077–2.177)*
Slope	−.004 (0.03)	1.551 (1.013–2.374)*
Intervention		1.449 (0.767–2.733)
DUDIT ≥ 2/6		2.901 (1.317–6.389)**
Impulsiveness		1.322 (0.959–1.822)
Variance component		
Intercept	54.42 (8.93)***	
Slope	.08 (.02)***	
Alcohol use		χ^2 (3) = 8.25, $p = 0.04$
Baseline	.03 (.08)	
Intercept	1.64 (0.21)***	1.780 (1.204–2.631)**
Slope	−.014 (.007)	1.365 (0.917–2.030)
Intervention		1.699 (0.859–3.361)
DUDIT ≥ 2/6		2.357 (1.034–5.377)*
Impulsiveness		1.307 (0.943–1.810)
Variance component		
Intercept	3.02 (.54)***	

(*Continued*)

Table 3. Continued.

Variables	Analysis of change	Analysis of recidivism
	Estimates (SE)	Hazard ratio (95% CI)
Slope	.002 (.0007)***	
Alcohol urge		χ^2 (3) = 5.31, p = 0.15
Baseline	.02 (.07)	
Intercept	1.23 (0.23)***	1.501 (1.012–2.226)*
Slope	−.007 (0.008)	1.148 (0.793–1.661)
Intervention		1.297 (0.661–2.692)
DUDIT ≥ 2/6		2.478 (1.094–5.606)*
Impulsiveness		1.389 (0.994–1.940)
Variance component		
Intercept	3.15 (0.55)***	
Slope	.004 (0.0009)***	
Drug use		χ^2 (3) = 8.79, p = 0.03
Baseline	−.008 (0.10)	
Intercept	1.08 (0.21)***	1.595 (1.164–2.186)**
Slope	.004 (.008)	1.522 (1.050–2.206)*
Intervention		1.588 (0.822–3.066)
DUDIT ≥ 2/6		2.472 (1.089–5.613)*
Impulsiveness		1.327 (0.965–1.826)
Variance component		
Intercept	3.69 (0.63)***	
Slope	.004 (.0009)***	
Drug urge		χ^2 (3) = 6.38, p = 0.09
Baseline	.29 (.08)***	
Intercept	.90 (.26)***	1.425 (1.068–1.899)*
Slope	.0001 (0.008)	1.016 (0.772–1.338)
Intervention		1.181 (0.621–2.247)
DUDIT ≥ 2/6		2.378 (1.040–5.426)*
Impulsiveness		1.333 (0.947–1.877)
Variance component		
Intercept	3.86 (0.64)***	
Slope	.003 (.0008)***	
Rating of most stressful everyday event		χ^2 (3) = 6.38, p = 0.09
Baseline	.03 (.066)	
Intercept	2.45 (.31)***	1.560 (1.029–2.366)*
Slope	−.03 (.011)*	1.581 (1.028–2.432)*
Intervention		1.482 (0.770–2.852)
DUDIT ≥ 2/6		2.789 (1.251–6.217)*
Impulsiveness		1.344 (0.988–1.828)
Variance component		
Intercept	3.66 (.65)***	
Slope	.008 (.002)***	

Note: 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 survival analysis of recidivism in crime, here presented as hazard ratios, and likelihood ratio test.
*$P \leq .05$; **$P \leq .01$; ***$P \leq .001$.

Together with previous findings reported from Andersson et al. (2014) and Vasiljevic et al. (2017), the results in this study imply that IVR-based ambulatory assessment may be a feasible method to assess everyday stress-related variables in the time immediately following release from prison. 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 release from prison.

Most importantly, IVR methodology has the potential to expand the range of rehabilitative resources available for offenders released from prison. One of the many benefits of IVR-based systems is that they can automatically provide personalised feedback and behaviour change instructions based on the individual's assessment responses (Andersson et al., 2014). Personalised feedback about a client's substance use is often included in Motivational Interviewing sessions (Walters, Vader, Harris, Field, & Jouriles, 2009), and incorporates components from traditional treatment approaches, such as Relapse Prevention (Hendershot, Witkiewitz, George, & Marlatt, 2011). Given the few rehabilitative resources available for offenders released from prison, brief automated interventions may be a valuable, cost-efficient, way to reduce substance use, mental ill-health symptoms, and support the clients in acquiring adaptive coping strategies.

Methodological considerations

The practical value of incorporating self-report assessments in correctional decision-making has been questioned, due to concerns about deception and self-presentation bias (van Impelen et al., 2017; Walters, 2006). However, rather than dismissing offender self-reporting as inappropriate, a more appropriate approach would be to investigate how traditional risk assessment approaches and self-report methods can complement one another in different ways (Walters, 2006). Self-reports have many advantages over assessments based on a trained professional's ratings, including their efficiency in terms of time and cost, that no special skills are required to interpret results, and that they enable a consideration of treatment needs based on these ratings (Hendry, Douglas, Winter, & Edens, 2013). Practitioners in applied settings may lack adequate training/education to assess dynamic risk factors, which in turn can lead to low validity and provide a weak basis for decision-making (Svalin, Mellgren, Torstensson Levander, & Levander, 2017).

Concerns about the ability and willingness of marginalised populations, such as prisoners, drug users and clients with mental health problems, to comply with ambulatory research protocols, have been raised by researchers as well as clinicians (Trull & Ebner-Priemer, 2013). However, evaluations of the AA literature demonstrate that electronic ambulatory assessments are a feasible way of collecting real-time data for a variety of populations, even for marginalised populations, such as individuals of low socioeconomic status, drug users, and individuals suffering from psychopathology (Shiffman, Stone, & Hufford, 2008). To the authors' knowledge, this study together with those of Andersson et al. (2014) and Vasiljevic et al. (2017) are the only studies using an AA approach to assess rapidly changing risk factors among released prisoners.

Missing data could rarely be avoided when the subjects are asked to complete daily diaries. However, most participants were compliant with answering the daily telephone assessments and the amount of missing data in this study was low. Growth modelling is a flexible statistical tool for repeated measurement data that has the advantage that it can be estimated in the presence of missing data, although the missing data must be characterised as missing at random. When there are missing but relatively complete data, the missing data is estimated by using the conditional distribution of the other variables, i.e. maximum likelihood method (Kang, 2013).

A critical question in all studies is the representativity of the sample studied. Screening results from previous studies on the same sample as in this study show that mental health problems, substance use problems, and traits indicative of antisocial and psychopathic behaviour frequently occur in this sample and are comparable to frequencies found in the general population of Swedish prisoners (Vasiljevic et al., 2017). For example, in the

Swedish prison system, an estimated 66% of prisoners suffer from a substance abuse problem (Hakansson & Berglund, 2012), a figure similar to the frequencies found in this sample (Vasiljevic et al., 2017). However, the generalisability of IVR-based self-report data to a wider offender population, as well as among different offender subgroup populations, needs further investigation.

Limitations

Several limitations of this study should be noted. Firstly, the self-report measures used in the present study do not include all empirically identified risk-need factors relevant to an overall evaluation of recidivism prediction and its management (Andrews & Bonta, 2010). For example, data covering historical and situational aspects of the participant's criminal behaviour (e.g. age at first conviction, number of previous convictions/crimes, sentence length, location, people in the immediate environment, etc.) was not included in this study.

This study was originally not designed to provide a comprehensive assessment of recidivism risk, but rather to investigate if IVR could be used to assess and intervene on the development of everyday stress-related variables among offenders in the immediate time following release from prison. Future studies should be expanded to consider other variables that are theoretically or empirically related to imminent offending (e.g. anger, immediate associates).

Secondly, there is some discrepancy in results between this and previous studies conducted on the same sample, which may be attributed to the characteristic of the sample. The studies by Vasiljevic et al. (2017) and Vasiljevic et al. (2017) featured samples of 106 and 93 respectively, in contrast to the reduced sample of 90 considered here. Furthermore, post-recidivism information on acute dynamic risk was terminated for this study, resulting in slightly different estimated values of change in acute dynamic risk, as well as slightly different association between the acute dynamic risk studied and recidivism in crime, compared to Vasiljevic et al. (2017).

Thirdly, the relatively small sample size and the limited follow up period may have impacted the prevalence of recidivism detected, as well as the overall statistical power to detect effects.

Fourthly, in the growth model analysis used here, only linear change is investigated. If a linear model does not capture within-person change processes, it may be appropriate to move to models with higher-order polynomial components. Although these models may better capture change patterns, difficulties arise in interpretation, especially when higher order slopes are added as predictors of recidivism in crime. Further, including interaction terms in the growth model analysis 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.

Fifthly, the intensive daily assessments during the one-month follow up may have limited the assessment of change for some participants in the study, particularly for those participants whose trajectory of change is more gradual. 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).

Sixthly, 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

In conclusion, this study together with Andersson et al. (2014) and Vasiljevic et al. (2017) shows that daily stress-related variables can be assessed and influenced using IVR, and that the technology can be used among paroled offenders. IVR technology has the potential to strengthen correctional practice, and extend research methods, in a cost-effective manner, which should be the goal of all correctional and forensic innovations.

Notes

1. The total score ranges from 0 (maximum negative) to 171 (maximum positive).
2. This study follows the guidelines in Singh, Yang, Mulvey, & the RAGEE Groups (2015) on what should routinely be reported in risk assessment research.
3. The number of parameters 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.
4. Participation in the study was terminated once the prisoner had re-offended or the one-month data collection following parole had been successfully completed.
5. The difference in response rates between recidivists and non-recidivists was not statistically significant after excluding those subjects that reoffended prior to the end of the 30-day follow-up period.
6. Even after daily drug use was subtracted from summary score, the slope was still significantly related to recidivism in crime (HR = 1.467, CI = 1.009–2.132, $p < 0.05$), and the model as a whole showed incremental improvement beyond the stable risk factors impulsiveness and problematic drug use (χ^2 (3) = 8.03, $p < 0.05$).

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