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The Dynamic Prediction of Antisocial Behavior Among Forensic Psychiatric Patients

A Prospective Field Study

Vernon L. Quinsey
Queen's University at Kingston, Canada
G. Brian Jones
Mental Health Centre, Penetanguishene, Canada
Angela S. Book
Kirsten N. Barr
Queen's University at Kingston, Canada

Staff ratings of 595 supervised forensic psychiatric patients on the Proximal Risk Factor Scale and the Problem Identification Checklist were completed monthly for an average of 33 months. During the follow-up, there were 265 incidents, 86 of which were violent. The average ratings, excluding those from the index month, differentiated patients who had incidents from those who did not. As well, the average ratings distinguished between individuals with and without incidents of a violent or sexual nature. There were significant increases in staff ratings in the months preceding the index incident month. Within-patient analyses showed that changes in dynamic risk scales comprising the best items for predicting incidents of any kind and violent or sexual incidents were strongly related to their respective outcomes and were significantly related to outcome in an independent sample. Changes in monthly staff ratings predict the imminent occurrence of antisocial and violent behaviors.

Keywords: *dynamic risk; reoffending; forensic psychiatric patients; risk appraisal; violence*

Risk appraisal is a central concern in the supervision and management of individuals with histories of violent and antisocial behaviors, whether they are in the correctional or mental health system (Quinsey & Walker, 1992). Decades of research have led to the development of actuarial instruments for the estimation of the long-term likelihood of antisocial outcomes among offenders released from institutions (Quinsey, Harris, Rice, & Cormier, 2005; Swets, Dawes, & Monahan, 2000). Although the accuracy of these instruments has been impressive in cross-validation (Harris et al., 2003), responsible day-to-day management of dangerous individuals requires not only awareness of long-term risk but also sensitivity to short-term changes in the likelihood of reoffending. Unfortunately, the development of instruments to measure changes in dynamic risk has lagged behind the development of actuarial instruments based on static or historical predictors.

There are several reasons for the slow development of dynamic risk instruments. First, the adjective *dynamic* has been confusingly applied to two quite different classes of changing events. The first class of predictors referred to as "dynamic" comprises those that can change or be made to change before a follow-up period begins. Prerelease exposure to treatment and response to treatment are examples of this kind of dynamic variable. Although these dynamic predictors reflect malleable phenomena, they function like static predictors in prediction research because when they occur they cannot be changed and do not change during the follow-up period. These predictors can be used to estimate the likelihood of recidivism during a follow-up period of any desired length. Thus, although change in the prerelease period can be measured and related to postrelease outcome, this change is nevertheless over at the time the follow-up period begins. Because of this, these malleable postadmission but prerelease variables can and should be treated analytically like any other historical predictor—they might be called *temporally fixed dynamic variables*. In contrast, the second class of dynamic predictors, variable postrelease predictors,

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are dynamic during the follow-up period. They include phenomena such as being intoxicated (as opposed to being an alcoholic, a static predictor), variations in mood, environmental precipitants (e.g., a threat or disappointment), and variations in opportunity to reoffend occasioned by changes in type or level of supervision or availability of potential victims (Zamble & Quinsey, 1977).

Second, research on potential dynamic predictors has suffered from variations in the specification of the follow-up or outcome internal—that is, some studies predict whether someone will become violent in the next 3 mins, others in the next 2 weeks, the next 2 months, or even the next 2 years. It is not at all clear that the same predictors would be equally applicable for all of these follow-up intervals. There has been extensive work on the immediate precipitants of violent behavior (for a review, see Quinsey, 2000). For example, enough information has been gathered from the examination of aggressive incidents involving psychiatric nursing staff that they can be successfully trained to avoid such incidents (Rice, Harris, Varney, & Quinsey, 1989). Although this research has informed the management of high-risk individuals, it has generally not yielded probability estimates of the likelihood of aggressive incidents, in part because interventions are of sufficiently low cost and short duration to obviate the need for them and the time to implement them so brief. Thus, the issues involved in predicting whether someone will become violent in the ensuing few minutes are very different from those involved in estimating the likelihood with which the same person will commit at least one new violent or sexual offense in the next 10 years of his opportunity to do so. In the case of dealing with imminent violence, one is not ordinarily concerned with an individual's probability of offending over a long time period or with his level of dangerousness relative to his peers, but rather with the meaning of changes in this person's behavior as they occur. The question, then, is primarily one of within-subject changes. All offenses, like all behaviors, have contemporaneous causes; even the highest risk individual is not violent all the time. This means that static risk factors and postrelease dynamic risk factors do not compete for outcome variance—they address very different issues. Static risk factors estimate the long-term likelihood of an individual committing at least one antisocial event of a specified type. Changes in dynamic risk factors signal whether the immediate likelihood of an antisocial event occurring is increasing, decreasing, or staying the same.

Studies of dynamic prediction have varied in terms of not only the follow-up period but also in the period during which change in the predictors has been measured. One interesting and potentially important class of dynamic predictors involves behaviors that change relatively slowly, over weeks or months. These predictors have received very little empirical or conceptual attention to date. However, they are of vital importance because they change slowly enough to be used by clinicians as treatment targets or signals that changes in supervision are required. In one of the first investigations of this class of predictors, Quinsey, Coleman, Jones, and Altrows (1997) coded a variety of predictors from the narrative documentation in the files of supervised forensic psychiatric patients in the month before they committed an antisocial act (eloping, eloping and committing a nonviolent offense, or committing a serious violent offense in the community) and compared these with the same predictors coded from the files in a 1-month period that occurred a year earlier. Within-patient analyses of scales derived from the narrative records showed that increases in antisocial attitudes and noncompliance preceded antisocial acts in general and serious violent acts in particular.

The scales derived from Quinsey et al.'s (1997) retrospective study were then employed in a prospective 16-month follow-up of 58 men with intellectual disabilities and histories of serious antisocial behaviors, who were residing in institutions about to be closed (Quinsey, 2004; Quinsey, Book, & Skilling, 2004). During the follow-up, 67% of these men exhibited antisocial behavior of some kind, and 47% exhibited hands-on violent or sexual misbehaviors directed toward other clients or staff in their community settings. The Violence Risk Appraisal Guide (VRAG; Quinsey et al., 2005), an actuarial instrument, was the best static predictor of the commission of at least one new violent or sexual incident, although a variety of other prerelease predictors coded from files were related to the likelihood of antisocial incidents of any kind. In the Quinsey et al. (2004), the same variables that had previously been coded retrospectively from files were rated each month by staff members who were in a position to observe client behavior. Changes in these monthly staff ratings of client characteristics were prospectively related to antisocial incidents; however, statistical power was too limited to make finer grained predictions of violent incidents. The current study examined the same predictors in a field trial large enough to yield sufficient statistical power.

We also designed the current study to address one further shortcoming of previous research on dynamic risk factors—the method of data analysis. Many traditional inferential statistics are designed to assess group differences, but at only one point in time. In recent years, analyses designed to model growth or change over time have become more popular (e.g., hierarchical linear modeling, growth curve modeling). These types of analyses typically look for commonalities in participants' developmental trajectories to make inferences about particular developmental pathways and the factors that may influence these pathways. However, these procedures are not designed to look for the group differences that are often of interest to psychologists. Nagin and his colleagues (Jones, Nagin, & Roeder, 1998; Nagin, 1999) have developed a procedure that combines growth curve modeling (i.e., tracking change over time) with the ability to look for distinct clusters or groups within the growth curves, and to assess what characteristics define these distinct groups; that is, this procedure can be used when the population does not constitute a continuous distribution, as is assumed in other growth curve modeling techniques but is rather a mixture of different groups defined by different probability distributions.

The current study was a field investigation of staff ratings of dynamic predictors in a large multisite sample of forensic psychiatric patients. The dynamic predictors assessed were those that were most predictive of new offenses in Quinsey et al.'s (1997) retrospective study. The current study was designed to answer three questions: first, were dynamic predictors related to violent offenses and antisocial behaviors of any kind under field conditions in which regular staff completed the ratings having received little or no training in doing so; second, which of these predictors were best suited to this purpose; and third, to what degree did the dynamic predictors operate in the same manner among offenders who varied in their levels of static risk? In addition to traditional ANOVAs, the current study also included trajectory analyses that, according to Nagin (1999), are designed for analyzing repeated measures data when

> the [behavior of interest] does not vary regularly across population members. Instead trajectories vary greatly across population subgroups in terms of the level of behavior at the outset of the measurement period and in the rate of growth and decline over time. (p. 153)

Method

Participants

Our sample comprised forensic psychiatric patients who had been found not criminally responsible on account of mental disorder or unfit for trial. The disposition of these patients, including release and minimum amount of mandatory supervision, was controlled by a provincial Review Board. During the period of the study, follow-up data were collected for 595 patients. Of these, 565 provided data for at least 6 months. However, because of missing data (e.g., having data for only one of the two instruments, or having missing items), the sample size varies between months. There were 467 male patients and 64 female patients in the current study (information on the sex of a number of individuals was missing). The average age of the sample was 42.21 years (*SD* = 11.05). Patients could have up to three psychiatric diagnoses. In total, 391 patients had a diagnosis of psychosis (74.6% of whom were diagnosed with schizophrenia), 61 had a mood disorder diagnosis, 148 were diagnosed as personality disordered, 39 were diagnosed with mental retardation, and 219 had other diagnoses. General medical diagnoses were not coded. In terms of the most serious offense leading to admission, 21% had been charged with homicide, 41% with a nonhomicidal violent offense, 5% with a sexual offense, 8% with an economic offense, 14% with other offenses (which included breach of probation, public mischief, causing a disturbance, threats, and harassment). Data were missing on the offense leading to admission for 11% of the individuals.

Measures

We used two different measures of dynamic risk in the current study, consisting of a number of variables that had demonstrated predictive validity in previous research. One set of variables had earlier been developed for treatment program planning (Rice, Harris, Quinsey, & Cyr, 1990) demonstrated reliable increases before antisocial incidents and in a retrospective study (Quinsey et al., 1997). The second set of variables was suggested to us by clinicians in the same retrospective study (Quinsey et al., 1997). These also showed reliable increases in the month preceding an incident. Because there was no reason to prefer one set or the other, and because so little research has been done previously on dynamic risk predictors, we cast a wide net, including all of the variables that showed promise in predicting incidents. We therefore created two dynamic risk instruments for evaluation in field trials. These same instruments had been used in the dynamic risk study of developmentally handicapped men (Quinsey et al., 2004).

The Problem Identification Checklist (PIC; Rice et al., 1990) was originally designed to be completed by staff who were well acquainted with the patients whom they were rating. The PIC has also been scored from narrative file records of staff observations (Quinsey et al., 1997). We used shortened versions of four of the five PIC subscales (Life Skills Deficit was not used) in the current study. The shortened version of the Inappropriate and Antisocial Behaviors subscale has 10 items such as, “Lack of consideration for others: Callousness, little empathy—anything that shows an attitude of thinking only about their own concerns and never of the thoughts, feelings of, or consequences for, other clients or staff." The second subscale is the 6-item Psychotic Behaviors subscale that concerns symptoms of major mental disorder (e.g., "Inappropriate suspicion: Must definitely be inappropriate, e.g., belief that food is poisoned, aliens are reading his thoughts, or 'everyone is out to get him.' In some cases because of the nature of the client's offense, his personality, or some physical abnormality, other clients may 'pick on' him, and the client's suspicions are possibly correct"). The third subscale, Mood Problems, contains 4 items, for example, "Anxiety: Expressions of excessive fear and worry, even for minor problems." The fourth subscale is Social Withdrawal containing 6 items (e.g., "Social withdrawal: Avoids contact with others deliberately [as compared to others avoiding him]"). All items in the shortened version of the PIC were rated on a 5-point scale ranging from 0 (*no problem*) to 4 (*severe problem*), so that higher scores indicated more problematic behavior.

The Proximal Risk Factor Scale (PRFS; Quinsey et al., 1997) also contains four subscales. We also used a shortened version of the PRFS in the current study. In this version, the Dynamic Antisociality contains 10 items that are similar to those in the Inappropriate and Antisocial Behaviors subscale (e.g., "Takes no responsibility for behavior: Tries to blame others or circumstances for his/her acts or problems. Sees him/herself, inappropriately, as a victim"). The second subscale, Psychiatric Symptoms, has 2 items dealing with symptoms of serious mental illness and is similar in content to the PIC subscale, Psychotic Behaviors. The third subscale, Poor Compliance, contains three items (e.g., "Poor compliance with current supervision restrictions: Late returning from pass. Drifts from group if out on group activity. Does not report when required. Does not deal with stressful or upsetting events in a constructive way, i.e., aggressive or self-defeating"). Finally, the Poor Medication Compliance/Dysphoria subscale is a two-item subscale concerning the issues described by its title. Items on the PRFS were also rated on a 5-point scale ranging from 0 (*no problem*) to 4 (*severe problem*).

Two single items were also included. An item called Denies All Problems ("Client denies all problems or just 'goes through the motions,'" Rice, Harris, & Quinsey, 1996) was included on the PRFS, which was completed by the nursing staff. The one-item Therapeutic Alliance Scale (Beauford, McNiel, & Binder, 1997) was included on the PIC and the PRFS and, therefore, was filled in by the nonnursing clinicians and the primary nurses. It featured descriptions ranging from very committed to therapeutic efforts (e.g., "Client is enthusiastically involved in treatment activities; recognizes and explores problem areas; seeks out staff assistance; makes realistic plans for the future") to treatment-resistant (e.g., "Client actively refuses most treatments; sees no purpose to the hospital stay; denies all problems; constantly demanding discharge").

Finally, the VRAG was completed using file data, in some cases by the site coordinator or another staff member from the hospital, and in other cases by one of the study authors (KNB or VLQ). The VRAG is a 12-item actuarial scale originally developed to predict violent and sexual recidivism among adult offenders released from correctional and forensic psychiatric institutions (Harris, Rice, & Quinsey, 1993) and subsequently validated on a variety of populations (Quinsey et al., 2005). Total VRAG scores can range from –26 to +38; however, these are usually divided for clinical purposes into nine equal-sized intervals (called bins), ranging from 1 to 9. In the current study, we had access only to the bin scores, not to the raw scores, on 198 patients. The use of bins rather than new scores limited the size of the predictive relationship we could find between the VRAG and incidents.

Procedure

At the time of joining the study, a site coordinator at one site in Nova Scotia, Canada, and each of eight sites in Ontario, Canada, identified those forensic patients for whom the psychiatric hospital administrator had exercised the discretion authorized by the review board to grant off-ward privileges. The site coordinator then assigned a unique identification number to each patient such that no individual could be identified using that number by anyone excepting the person making the assignment. Because of the use of identification numbers, we could not determine whether the same individuals were transferred between sites. Individuals who were discharged from one site and readmitted to another would appear in the new site with a different identification number. However, because there were very few transfers between sites, this occurred very rarely, and records pertaining to an individual identification number were treated as if they had come from a different patient.

At the time each patient joined the current study, the site coordinator completed a Patient Registry Form, which provided the patient's unique identification number, the patient's birth date and sex, and details of any diagnoses and the offenses for which the patient had been admitted. Thereafter, each month, the clinical staff of the site registering the patient completed the PRFS (Quinsey et al., 1997) and the PIC (Rice et al., 1990).

These assessments were completed by the individual staff members most familiar with the patient, based on their experience with the patient in the previous month, and not by teams of clinicians in a conference format. The PIC was completed by the nonnursing clinician (e.g., psychologist, psychiatrist, social worker, etc.) most closely involved with the patient's care and supervision. In cases where this clinician was the only person so involved, the PRFS was substituted for the PIC. The PRFS was completed by each patient's assigned primary or secondary (associate) nurse. Where no such assignment had been made, such as for some patients who lived in the community, the PRFS was completed by the clinician having the most contact with the patient. Raters also recorded each patient's current level of supervision and current psychiatric medications on these forms.

Finally, any time an incident (i.e., elopement, violation of conditions of supervision, illegal or aggressive act) occurred, one of the staff members in charge of supervising the patient completed an Incident Report Form. On this form, they recorded the date, nature, and type of incident (e.g., property, nonviolent, violent, sexual, etc.), the details of any victims and victim injuries, and any charges brought against the patient as a result of the incident. Hospital staff forwarded these forms to the researchers, generally at the same time as the next month's data were sent.

Results

The 595 forensic psychiatric patients were followed for an average of 33 months (*SD* = 14.67) and a maximum of 54 months. For most of the analyses that follow, 30 individuals were excluded because of missing data (e.g., they had fewer than 6 months of follow-up data). These 30 were, however, included in the trajectory analysis. Sample size for different variables ranged from 531 to 565 because of missing data. Nearly one half of the participants (254/531) lived in the community at some point in time. However, they generally lived in supervised facilities, such as group homes or halfway houses, and staff at these residences reported any significant legal or psychiatric problems to hospital staff, who completed incident report forms, or directly to the researchers. Thus, we were fairly confident that only minor incidents would be missed. There were 265 incidents during the 54-month period. Of these, 86 were violent incidents (excluding threats, attempted assaults, and property destruction), 52 were escapes or escape attempts, 37 were nonviolent offenses, and 6 were hands-on sexual offenses (hereafter coded as violent offenses). The remaining incidents were minor and not clearly specified. In terms of the percentage of the sample who had incidents, 143 patients (or 24%) had incidents of any kind; all of these patients could be included in within-patient analyses of incidents of any kind because they had at least two incident-free months preceding an incident. There were 70 patients (or 12% of the sample) who had violent incidents; however, only 42 of these patients had at least two incident-free months preceding a violent incident and so could be included in the within-patient analyses.

Psychometric Properties of the Scales

Internal consistency. Alpha coefficients for all of the subscales were calculated for each month at each site. Monthly coefficients were computed to avoid violating the assumption of independence of observations. The coefficients were then averaged over months and sites. Resulting alphas were generally moderate to high: Psychotic Behaviors .79, Inappropriate Behaviors .70, Mood Problems .61, Social Withdrawal .76, Dynamic Antisociality .91, Psychiatric Symptoms .73, Poor Compliance.52, and Medication Noncompliance/Dysphoria .45. The last two low reliability coefficients were for scales of two or three items.

Interrater reliability. Because the PIC and PRFS were filled out by different people (clinical staff and front-line staff, respectively), correlations between similar subscales could be calculated to establish interrater reliability. The correlations between similar subscales were all moderately large, particularly given the small number of items involved. The Psychotic Behaviors subscale of the PIC was significantly positively correlated with the Psychiatric Symptoms subscale of the PRFS, $r_{\text{pb.ps}} = .56$, $p < .01$. Similarly, the Inappropriate Behaviors subscale of the PIC was correlated with Dynamic Antisociality, $r_{\text{ib.da}} = .41$, $p < .05$. Finally, Mood Problems were significantly correlated with Medication Noncompliance/Dysphoria, which contains items relating to anger and anxiety, $r_{\text{mp.mc}} = .45$, $p < .05$. The average correlation between the Therapeutic Alliance Scale filled out by the front-line and non-front-line staff was .57.

Differentiation of Patients With and Without Incidents

Several between-patients analyses were carried out to ascertain whether there were significant differences between patients who had incidents and patients who did not; these analyses included all of the patients. As predicted, patients who had an incident of any type had significantly higher static risk levels (as indicated by the VRAG bins) than did patients who had no incidents, $t(196) = -2.78$, $p = .006$, $d = .46$. In addition, the data show that patients who had incidents of any kind showed higher average levels of dynamic risk than did patients with no incidents. As expected, patients who had incidents received higher staff ratings on most subscales of the instruments than did patients who had none (see Table 1). In these analyses, ratings were averaged over all months that did not contain an incident (index months were excluded to eliminate retrospective bias). Similarly, patients with incidents had more variable ratings on most subscales than did patients with none. The corresponding effect sizes in these analyses ranged from small to medium.

Although there was a trend for the probability of a violent incident to increase with higher VRAG bins, patients who had a violent incident did not have significantly higher VRAG scores than patients without incidents, $t(196) = -1.31$, $p = .19$, $d = .30$. However, as shown in Table 2, most of the subscales of the instruments scored during the follow-up period reliably distinguished between patients with and without violent incidents, with those patients who had violent incidents having significantly higher means on all of the subscales than did patients with no incidents. Finally, patients with violent incidents had more variable ratings over months on most subscales than did those without any. Effect sizes for violent incidents were virtually identical to those for any incident, ranging from small to medium.

Prediction of Incidents from Dynamic Within-Patient Variables

Within-patient (or repeated measures) analyses were conducted to assess whether patients who had incidents showed changes in their dynamic risk levels in the months leading up to the incidents; these analyses included only patients who had incidents. These analyses comprised two comparisons: the previous months (the average of up to 6 months preceding the prior month) versus the prior month (the month immediately preceding the index month); and the prior month versus the index month. The comparison between the previous months and the prior month is the most important because it could not be contaminated by retrospective bias. The average of the previous months did not include any months in which an incident occurred. Comparisons between index month ratings and ratings for either the previous months or the prior month were potentially subject to retrospective bias because ratings from the index month may have been inflated if they were made after an incident took place.

Table 1
Comparison of Patients With and Without Any Incidents

Scale	Incident?	*n*	*M*	*SD*	*t* value	*p* value	Cohen's *d*
Problem Identification Checklist							
Psychotic Behaviors	No	363	3.22	4.03	–1.12	.26	0.10
	Yes	134	3.69	4.23			
Inappropriate Behaviors	No	358	3.97	4.58	–4.45	< .001	0.40
	Yes	133	6.11	4.80			
Mood Problems	No	363	1.38	1.74	–4.50	< .001	0.41
	Yes	133	2.23	1.91			
Social Withdrawal	No	362	4.14	4.12	–2.50	.01	0.23
	Yes	135	5.20	4.23			
Therapeutic Alliance	No	324	1.29	0.95	–2.41	.02	0.23
	Yes	121	1.52	0.90			
Proximal Risk Factor Scale							
Dynamic Antisociality	No	403	7.04	7.46	–4.12	< .001	0.35
	Yes	140	10.34	8.40			
Psychiatric Symptoms	No	398	1.05	1.70	–2.07	.04	0.18
	Yes	139	1.41	1.75			
Poor Compliance Medication	No	402	1.09	1.41	–5.43	< .01	0.47
	Yes	140	2.02	1.84			
Medication Noncompliance/Dysphoria	No	401	1.10	1.19	–5.22	< .01	0.45
	Yes	139	1.82	1.48			
Denies all Problems	No	406	1.10	1.02	–2.96	.003	0.25
	Yes	140	1.41	1.06			
Therapeutic Alliance	No	324	1.29	0.95	–2.41	< .01	0.23
	Yes	121	1.52	0.90			

Table 2
Comparison of Patients With and Without Violent Incidents

Scale	Incident?	*n*	*M*	*SD*	*t* value	*p* value	Cohen's *d*
Problem Identification Checklist							
Psychotic Behaviors	No	431	3.15	3.85	–2.27	.005	.20
	Yes	66	4.66	5.22			
Inappropriate Behaviors	No	425	4.18	4.58	–4.10	< .001	.37
	Yes	66	6.90	5.06			
Mood Problems	No	430	1.49	1.79	–3.70	< .001	.33
	Yes	66	2.39	1.84			
Social Withdrawal	No	430	4.20	4.05	–2.90	.002	.26
	Yes	67	5.93	4.61			
Therapeutic Alliance	No	390	1.30	.93	–3.11	.002	.30
	Yes	55	1.73	.95			
Proximal Risk Factor Scale							
Dynamic Antisociality	No	474	7.31	7.57	-4.25	< .001	.37
	Yes	69	11.90	8.50			
Psychiatric Symptoms	No	468	1.05	1.67	–2.97	.001	.26
	Yes	69	1.78	1.92			
Poor Compliance Medication	No	473	1.18	1.43	–4.58	< .001	.39
	Yes	69	2.38	2.11			
Medication Noncompliance/Dysphoria	No	472	1.16	1.21	–4.83	< .001	.42
	Yes	68	2.14	1.60			
Denies all Problems	No	477	1.12	1.03	–3.65	< .001	.31
	Yes	69	1.60	1.00			
Therapeutic Alliance	No	447	1.12	.91	–4.29	< .001	.38
	Yes	64	1.67	.96			

Analyses were done first for individuals with any incident, and then for those with violent incidents. Scores on most subscales increased leading up to an incident and leading up to a violent incident (see Table 3). When predicting any incidents, for the key comparison between the prior month and the average of the previous months, the Dynamic Antisociality, Poor Compliance, and Therapeutic Alliance Scales of the PRFS showed significant increases prior to the incident. When predicting violent incidents, only the Inappropriate and Antisocial Behaviors and Therapeutic Alliance Scales of the PIC increased significantly before the violent incident.

New Dynamic Risk Appraisal Scale

Item analyses. The individual items from both measures were run through a dependent-samples t test comparing the prior month to the (up to 6) previous months. Any items that increased in value and showed a p value of less than .25 were retained for the new scale. This liberal retention criterion was adopted for the purposes of scale construction. Analyses were conducted separately for any incident and violent incidents. The items were then combined into one scale, the Dynamic Risk Appraisal Scale, that contains two subscales, one for assessing general risk level and one for assessing violence risk levels. For general risk, the analysis resulted in a 23-item subscale, and for violence risk, a 10-item subscale. Copies of the Dynamic Risk Appraisal Scale and scoring instructions are available in Quinsey et al. (2005) or from the authors.

Properties of the new scale. Alpha coefficients for both of the new subscales were acceptable (.93 and .79 for the General and Violence Risk scores, respectively). The mean rating for the General Risk subscale was 16.89 (SD = 13.93) out of a possible 92 and for the Violence Risk subscale was 5.57 (SD = 5.03) out of a possible 40. Average ratings on these subscales (omitting index months) were correlated with the VRAG bin scores (r = .20, p = .014 for general risk and r = .17, p = .029 for violence risk).

The total scores from the new subscales formed by these analyses were calculated for each individual and were analyzed using repeated measures ANOVAs. Because of the way the items were selected, it was a foregone conclusion that the subscales would significantly correlate with the outcomes they were designed to predict. As shown in Table 4, general risk ratings rose in a linear fashion leading up to incidents of any type, and Violence Risk scores rose linearly leading up to violent incidents. Ratings

(text continues on p. 1556)

Table 3
Repeated Measures Analyses for Patients with Any Incidents and With Violent Incidents

Subscale	*n*	*p* Value	Linear *p*	Previous vs. Prior *p* Value	Previous vs. Index *p* Value	Prior vs. Index *p* Value
Any Incident						
Problem Identification Checklist						
Psychotic Behaviors	73	.02[a]	.01	.41	.01	.03
Inappropriate Behaviors	76	.003	.002	.06	.002	.07
Mood Problems	75	.04	.03	.11	.03	.26
Social Withdrawal	76	.02[a]	.01	.21	.01	.07
Therapeutic Alliance	54	.42	.25	.33	.25	.77
Proximal Risk Factor Scale						
Dynamic Antisociality	82	< .001[a]	< .001	.001	< .001	.006
Psychiatric Symptoms	73	< .001[a]	< .001	.38	< .001	< .001
Poor Compliance	83	< .001[a]	< .001	.02	< .001	< .001
Medication Noncompliance/Dysphoria	80	< .001[a]	< .001	.20	< .001	< .001
Denies all Problems	82	< .001[a]	< .001	.08	< .001	.001
Therapeutic Alliance	64	< .001	< .001	.04	< .001	.004
Violent Incident						
Problem Identification Checklist						
Psychotic Behaviors	24	.07*	.06	.93	.06	.08
Inappropriate Behaviors	25	.003	.002	.03	.002	.18
Mood Problems	24	.05	.02	.11	.02	.45
Social Withdrawal	25	.29	.58	.08	.58	.39
Therapeutic Alliance	20	.04	.06	.01	.06	.77

(continued)

Table 3 (continued)

Subscale	*n*	*p* Value	Linear *p*	Previous vs. Prior *p* Value	Previous vs. Index *p* Value	Prior vs. Index *p* Value
Proximal Risk Factor Scale						
Dynamic Antisociality	24	.004	.014	.79	.014	.011
Psychiatric Symptoms	20	.009	.13	.07	.13	.05
Poor Compliance	24	.11*	.08	.99	.08	.12
Medication Noncompliance/Dysphoria	24	.02*	.04	.38	.04	.02
Denies all Problems	24	.85*	.90	.77	.90	.73
Therapeutic Alliance	17	0.69	.47	.62	.47	.65

a. The assumption of sphericity was not met ($p < .01$), and the resulting p value is corrected using the Greenhouse–Geisser procedure.

Table 4
Repeated Measures Analysis of the Dynamic Risk Appraisal Scale (General Risk Subscale for Any Incidents and Violent Risk Subscale for Violent Incidents)

Type of Incident	*n*	Months	*M*	*SD*	Overall *p*	Linear *p*	Previous vs. Prior	Previous vs. Index	Prior vs. Index
Any	55	Previous	20.66	14.65	< .001	< .001	.001	< .001	.001
		Prior	25.81	17.39					
		Index	31.88	15.16					
Violent	26	Previous	8.95	5.63	.001	.002	.004	.002	.146
		Prior	11.59	7.31					
		Index	13.58	8.06					

for prior months were significantly greater than ratings for previous months for the relevant outcomes of both subscales.

Trajectory Analyses

To determine whether changes in the General and Violence Risk ratings were related to changes in the probability of an incident over time using data from all patients (not just those who had incidents), trajectory analyses were conducted using a SAS procedure (PROC TRAJ) developed by Jones et al. (1998). PROC TRAJ was developed to analyze repeated measures data (i.e., developmental trajectories) when the population is not continuously distributed on the predictors of interest but is made up of discrete groups with different probability distributions. This type of analysis applies in the current study because the dependent variable was discrete (incident vs. no incident) and was measured multiple times for each participant. The procedure allows for time dependent covariates to be entered into the model.

In the first step of the procedure, the model selection step, a maximum likelihood estimation procedure is used to determine the number of groups that best fits the data, and the proportion of individuals falling within each group. A polynomial relationship is presumed to exist between time and the behavior or measure of interest, and the parameters (or coefficients) of this polynomial relationship are estimated by maximization of a log likelihood function. A key feature of this type of analysis is that the coefficients of the parameters in this relationship are free to differ across groups. In other words, this analysis can detect whether the predictors operate differently in the distinct groups.

The criterion used to select the optimum number of groups is the Bayesian information criterion (BIC). The equation for the BIC is such that the value is always negative, so the maximum BIC is the least negative value returned. Nagin (1999) noted that the equation for the BIC also tends to reward parsimony; that is, although increasing the number of parameters will generally increase a model's fit, there is a penalty for the addition of parameters in the calculation of the BIC, so that any increase in model fit must be larger than the penalty for the model to be retained. In addition to the BIC, the Bayes factor can be calculated to assess the odds of a particular model being the correct one. A Bayes factor of 1 indicates that a particular model is as likely to be correct as the model to which it is being compared, whereas a Bayes factor of 10 indicates that the particular model is 10 times more likely to be correct. Thus, when two competing models are being compared, researchers assess the decrease in BIC associated with each model and the Bayes factor probability levels.

When the model that best fits the data is selected, individuals' posterior probabilities of membership in the different groups of the model can be calculated based on the model coefficient estimates. The posterior probabilities can then be used to create profiles of an average group member for each of the different developmental trajectories based on the predictors or covariates entered into the model, and the impact of these covariates on the likelihood of group membership can be tested statistically. The significance of the model coefficients is tested using a one-sample *t* test assessing the coefficient against the null hypothesis value of 0 in a manner similar to the procedure used to test beta coefficients in regression analyses.

The general risk ratings and whether the individual lived in the community were entered as time-dependent covariates in the model predicting an incident of any type. The Violence Risk ratings and the community variable were used in the model predicting only violent incidents. For these analyses, we included an additional 30 patients who were not included in the rest of the current study because they had fewer than 6 months of follow-up data. The total sample size for the trajectory analysis was 595 patients. Once again, ratings for the index month were not included in these analyses. In these analyses, a patient could have multiple incidents (but only one in a particular month).

General Risk

Model selection. The analysis of developmental trajectories uses the BIC to assess model selection. In the case of general risk, the change in BIC for 2 groups versus 1 group was very strong, $2\log(B_{10}) = 104.30$. Because a value of 10 reflects a large effect size, the value obtained was considered strong evidence for rejecting the null hypothesis (that a more succinct model would suffice). In other words, there was reason to believe that there were two separate groups in predicting incident probability over time. A three-group model produced an increase in the BIC, meaning that this model did not do as well as the two-group model at explaining the data points. Consistently, Group 2 showed a higher likelihood of having an incident and so was designated the high-risk group, whereas Group 1 showed little to no probability of having an incident and so was designated the low-risk group.

Tests of coefficients. Two regression equations, one for each group, predicting the probability of an incident in any given month resulted from the analysis. As mentioned above, the variables included as predictors were the

General Risk score for each month and whether the individual was living in the community that month. The predictors acted slightly differently for the two groups. For the low general-risk group (the group having a low probability of having an incident), both variables were significantly positively related to incidents. In other words, increases in general risk over successive months and moving into the community significantly increased the odds of having an incident, $b = .06$, $t(593) = 10.87$, $p < .001$, $d = .89$ and $b = 1.37$, $t(593) = 5.24$, $p < .001$, $d = 0.43$, respectively. However, for the high general-risk group (having a higher probability of incidents), only increases in the General Risk score over months predicted incidents, $b = .03$, $t(593) = 4.91$, $p < .001$, $d = 0.40$. In other words, the probability of a high general-risk group patient having an event in the next month increased by .03 (or 3%) for every unit increase in the General Risk score from the score of the previous month.

Group characteristics. What static variables, if any, distinguished between the two groups in the analyses of general risk? The low general-risk group comprised 90.5% of the sample (538 patients), leaving 9.5% in the high general-risk group (57 patients). All static variables (VRAG bin, the existence of mood, personality, and psychotic diagnoses, number of incidents, and sex) were compared across groups by *t* test or chi-square analyses. The only variable that significantly distinguished between the groups formed based on the General Risk score was the number of incidents the individual had, $t(561) = –26.18$, $p < .001$, $d = 2.92$. More specifically, individuals in the high general-risk group had significantly more incidents than did those in the low general-risk group. Attesting to the validity of the grouping procedure, average General Risk scores were significantly higher in high general-risk than in low general-risk patients, $t(442) = –3.10$, $p = .002$, $d = .51$.

Violence Risk

Model selection. For violence risk, the change in BIC for a two-group versus a one-group model was negative (i.e., the BIC score increased), indicating that the one-group model was more efficient than the two-group model. In other words, there was no reason to believe that there were separate groups in predicting violent incident probability over time. This means that the predictors acted similarly across patients.

Tests of coefficients. As in the trajectory analyses for general risk, the time-dependent predictors included Violence Risk scores and whether an individual lived in the community. Increases in violence risk over months resulted in an increased probability of having a violent incident, $b = .15$, $t(593) = 11.13$, $p < .0001$, $d = .91$. However, moving into the community was not related to probability of a violent incident as it was for incidents of any kind. This difference might have occurred because significantly fewer patients who had violent incidents were moved into the community than were patients with no violent incidents, $\chi^2(1) = 4.89$, $p = .027$. However, even though patients with violent incidents were less likely to be transferred to the community, at some point during the current study, nearly one third did make it into the community. It was noteworthy that the predictors appeared to act similarly across hospital and community settings.

Discussion

At the most general level, the current study was designed to answer three questions: Were dynamic predictors related to violent and/or antisocial behaviors; which of these predictors were best suited to this purpose; and, finally, to what degree did the dynamic predictors operate in the same manner among offenders who varied in their levels of static risk? The results provide at least tentative answers to each of these questions. First, changes in a number of dynamic predictors were reliably associated with antisocial or violent incidents. Second, the best of these, incorporated into the new Dynamic Risk Appraisal Scale, showed significant increases leading up to any incidents and violent incidents. Third, individuals who were already designated as high risk by virtue of their average dynamic risk scores showed significantly higher likelihood of having an incident of any type when they moved into the community; low-risk individuals did not show this pattern. Similarly, those who had higher static risk (i.e., higher VRAG bin scores) also tended to have higher dynamic risk scores (General and Violent), and higher probabilities of having any and violent incidents. In addition, patients who had any incident and patients who had violent incidents had significantly higher VRAG scores than patients who had no incidents. We now turn to a more detailed discussion of the results.

Static Predictors

In general, the findings of the current research were in line with expectations derived from our research on static and dynamic prediction. In terms of static risk, the VRAG was related to the occurrence of incidents of any type and to violent incidents, although only the former correlation was significant. The use of VRAG bins instead of actual scores and the large number of missing VRAG assessments reduced the statistical power of these comparisons.

The subscale scores can also be considered as static predictors differentiating between high-risk and low-risk patients when they were averaged over time (excluding ratings from the index months)—that is, the average of the scores from all nonincident months can be considered an overall risk score for each patient. The mean monthly staff ratings on most of the subscales strongly differentiated between patients who had incidents and those who had none, and between patients who had violent incidents and those who had none. The staff ratings of patients who had incidents of any kind and those who had violent incidents were also more variable over time than were the ratings of patients who had no incidents, suggesting that increasing magnitude of changes in ratings over time might be related to the occurrence of incidents.

Although the ratings on the PRFS yielded larger effect sizes than ratings on the PIC, it must be recalled that rating scale was confounded with type of rater; that is, it might be expected that nursing staff, who filled out the PRFS, would be more sensitive to changes in patient characteristics because they saw the patients more frequently than did the nonnursing staff.

Dynamic Predictors

Turning to dynamic prediction, increases in ratings on several subscales were related to the occurrence of incidents and violent incidents. Those subscales that were significant when the index month was excluded (i.e., that showed a change from previous months to the month prior to an incident) were Dynamic Antisociality, Poor Compliance, and Therapeutic Alliance (all from the PRFS) for incidents of any type and Inappropriate and Antisocial Behaviors and Therapeutic Alliance (from the PIC) for violent incidents.

The selection of the best items from all of the rating scales resulted in a 33-item Dynamic Risk Appraisal Scale, comprising a 23-item subscale for the prediction of incidents of any type and a 10-item subscale for the prediction of violent incidents. These two subscales were strongly related to their respective outcomes. The high alpha coefficients for these subscales indicate that, although the items originally came from different domains, there is considerable shared variance among them that is contributed by a common underlying construct.

The results of the trajectory analyses converged with, but also added to, the results of the ANOVAs. For the prediction of any incident the trajectory analyses supported the existence of two separate groups—those at high risk for committing new offenses and those at low risk. In each of these groups, increases in the General Risk subscale score significantly predicted incidents; however, being released to the community only predicted incidents in the low-risk group. For the prediction of violent incidents, the analyses did not suggest distinct groups of patients (although as Nagin, 1999, noted, this procedure tends to underestimate the number of groups because of its emphasis on parsimony). When predicting the likelihood of new violent offenses, only the score on the Violence Risk subscale was significant, showing that these items were similarly predictive whether the patient was in the community or in the hospital.

Because the items for the Dynamic Risk Appraisal Scale were identified based on their relation to outcome, cross-validation is essential. Fortunately, the data from the field study of high-risk men with intellectual disabilities described in the introduction (Quinsey et al., 2004) provides an opportunity for cross-validation because the same items were used in both studies, even though the samples were quite different. The General Risk subscale developed in the current study differentiated clients who had at least one incident from those who had none using the average of nonindex months, $t(55) = 2.45$, $p < .009$, one-tailed, and the Violence Risk subscale differentiated clients who had at least one violent incident from those who had none using the average of nonindex months, $t(55) = 2.08$, $p < .022$, one-tailed. With respect to detecting changing risk, the General Risk subscale increased between previous and prior months for any incident, $t(38) = 1.70$, $p = .052$, one-tailed. The Violence Risk subscale showed an increase between previous and prior months for violent incidents, $t(19) = 2.87$, $p < .006$, one-tailed.

Implications for Dynamic Risk Appraisal

Given that changing scores on the Dynamic Risk Appraisal Scales are associated with changes in risk, how might they be interpreted? A unit change in dynamic risk score reflects a change in the probability of an incident occurring in the near future. However, the overall probability of an event occurring is very different for individuals who have high as opposed to low baseline scores. The probability of at least one event of any type occurring each month for the approximately 10% of high-risk patients was .08, whereas the probability of an event occurring each month was .004 for the remainder. Therefore, even though the change in probability with a unit change in General Risk score from one month to the next is lower for the high-risk patients (.03) than the change for low-risk patients (.06), the absolute probability of high-risk patients' involvement in an incident is higher. The base rate situation for violent incidents was more extreme. The probability of a violent incident during the 54 months was .002. Each one-point increase in the Violence Risk score from one month to the next corresponded to a .15 (or 15%) increase in the probability of a violent incident in the next month, and this was true across all patients.

These statistics show that clinicians must take into account the absolute probability of an incident for a given patient (the base rate) and the amount of change in the risk score that has occurred. The base rate would be determined, as in the analyses for the current study, by the patients' average risk score or, alternatively, their actuarially determined level of static risk. An even simpler method might be to assign all of those individuals who have already had incidents to the higher risk category because having had an incident was also a good predictor of group membership (i.e., all of the high-risk group members had at least one incident).

Strengths, Limitations, and Future Prospects

A number of features of the current study strengthen confidence in its results. The difficulties in making predictions are well known, especially when the events to be predicted are rare (Grove & Meehl, 1996; Swets et al., 2000). In addition to the fact that the base rate of recidivistic incidents is already low, staff are trained to anticipate such events and to prevent them if at all possible, thus making the prediction task even more difficult. However, the current study was designed to overcome some of these difficulties. It was a large-scale, multisite study involving forensic psychiatric patients in a variety of hospitals and with a range of security and supervision structures, and the patients were followed for long intervals. Even with the factors mitigating against finding significant relationships, we were able to achieve significant discriminative and predictive relationships with some of the variables, which we then aggregated into new scales suitable for further research. In addition to the design of the current study, we used some novel statistical analyses that are specifically intended for the type of data we collected. The trajectory analyses enabled us to assess whether the high-risk group constituted a qualitatively different group from the low-risk group. The low-risk group had very few incidents whereas the high-risk group had many. In fact, the probability of an incident in the high-risk group was .08

in any given month; however, in the low-risk group it was .004. Thus, individuals in the high-risk group were 20 times more likely to have an incident. The conclusions from these analyses converged with those of the between-groups and repeated measures analyses, show that analyses designed to track patients' behavioral changes over time are useful for discriminating groups of differing risk levels, and identify the same distinct groups as do the more traditional analyses. It is important to be clear that we are not advocating the use of the Dynamic Risk Appraisal Scale as an actuarial instrument. The scale is designed to aid risk management decisions in which a high false-positive rate is acceptable (e.g., in short-term decisions, such as issuing weekend passes) and that it would be used by visually examining the direction and magnitude of changes over time for individual patients.

Additional strengths relate to the content and format of the scales. The items on the PRFS were derived initially from staff comments in the files of forensic patients who committed some sort of recidivistic offence. Thus, the behaviors that predict increasing risk are behaviors that are already being noted by hospital staff. In other words, staff members are recording a variety of behaviors, some of which predict increasing risk; they simply do not know to which behaviors they should attend. This means that observing and responding to changing risk levels does not involve introducing new requirements into staff routines—something that would no doubt encounter institutional resistance. Rather, the observations that staff members are already wont to make simply need to be filtered according to their predictive utility. This fact greatly increases the chance of institutional acceptance of the instruments. Finally, the instruments were designed so that staff could complete them without formal training. Item and response anchor descriptions were provided; however, no other training was given; in spite of this, there were significant correlations of moderate size between similar scales comprising different items completed by staff in different positions (e.g., psychiatrists, psychologists, nurses, social workers, occupational therapists, and clergy members). Interrater reliability of the scales, however, could be improved by training raters and by averaging scores obtained from independent raters.

Despite a large sample and successful use of the PRFS and PIC scales in previous studies, the method of item selection for the Dynamic Risk Appraisal Scale capitalized on chance. Although the Dynamic Risk Appraisal Scale functioned well on cross-validation on a sample of developmentally handicapped individuals, further testing of it in different settings is yet required. Monthly ratings were sufficient to demonstrate the operation of measurable, slowly changing dynamic risk factors. The temporal resolution of dynamic changes would, of course, be much better with weekly, or even daily, ratings. It is probable that larger predictive relationships could be obtained with more frequent observations, averaged over independent raters. Although we had one group of staff fill out the PIC and another the PRFS in this investigation, it is doubtful that this procedure is required. Presumably, front-line staff and nonnursing staff could complete the Dynamic Risk Appraisal Scale.

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Vernon L. Quinsey received his PhD in biopsychology from the University of Massachusetts at Amherst in 1970. He was first a psychologist and later director of research at the maximum security Oak Ridge Division of the Mental Health Centre in Penetanguishene, Ontario. In 1988, he moved to Queen's University in Kingston, Ontario, where he is currently professor of psychology, biology, and psychiatry and head of the Psychology Department.

G. Brian Jones is chief of the Forensic Division at the Mental Health Centre in Penetanguishene, Ontario. He holds academic appointments with the Departments of Psychiatry at McMaster University and the University of Toronto and sits as a member of the Ontario (Criminal Code) Review Board.

Angela S. Book is an assistant professor in the Psychology Department at Brock University. Her research interests include psychopathy, violent offending, empathy, and victim selection.

Kirsten N. Barr has a BSc (Hon.) in biopsychology from University of British Columbia and an MA in experimental psychology from Lakehead University. She is currently at work on a PhD in forensic psychology from Queen's University, in the area of evolution of antisocial behavior.