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A multiple risk factor approach for predicting DWI recidivism

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Abstract

A sample of DWI (driving while impaired) offenders was studied to compare various approaches for predicting reoffenses over a 4-year period. Logistic regression yielded multivariate predictor equations that were significant statistically, but were not helpful to clinicians in assessing risk for reoffending. As a different approach, five predictor variables that were consistently correlated with reoffense status were examined to determine the cut score at which the repeat offense rate exceeded the base rate. These were combined to yield the number of risk factors (from 0 to 5) for each offender. This method, used for the original and a hold-out sample, yields results as accurate as those derived from a logistic regression model that includes all the risk variables, and allows clinicians to classify offenders into low and high risk categories in a straightforward manner. Nearly half of offenders with four or five risk factors (age, years of education, arrest blood alcohol concentration (BAC), score on the receptive area scale of AUI and raw score on the MacAndrews scale of MMPI-2) were rearrested compared to the base rate (25%). However, this method is not sufficiently precise to accurately predict which individuals will and will not be rearrested. Although generalizability of specific algorithms across populations needs to be examined, this method appears promising as a clinically accessible way to classify, in a given offender population, those who are most likely to repeat the offense.

Keywords: DWI; DUI; Recidivism; Alcohol

1. Introduction

Few question the seriousness of driving while impaired (DWI) by alcohol as a social problem in the United States. Despite encouraging reductions in alcohol-related mortalities over the past two decades (National Highway Traffic Safety Administration, 1997a), DWI remains a major preventable cause of death, particularly among young people.

Most people who are arrested for a DWI will not repeat the offense, yet about one-third of all drivers arrested for DWI are repeat offenders (ROs) (National Highway Traffic Safety Administration, 1997b). The efficacy of exposing all DWI offenders to "preventive" interventions is poorly understood, and the risk is that exposing offenders to standard interventions such as large DWI "schools" could desensitize newer offenders and actually increase the risk of recidivism. It would be useful, then, to identify predictors of reoffense so that interventions could be targeted rather than universal.

Various methods have been tried for differentiating recidivists from the less at-risk majority of offenders. Multivariate analyses such as discriminant function analysis and logistic regression have become particularly popular, yielding complex equations to classify individual cases (Peck, Arstein-Kerslake, & Helander, 1994; McMillen, Adams, Wells-Parker, Pang, & Anderson, 1992; Arstein-Kerslake & Peck, 1985; Burch, 1974; McGuire, 1975, Ellingstad, 1974). The resulting classification systems, while able to categorize individuals at a level significantly better than a coin toss, are complex and difficult to put into clinical practice. That is precisely the problem we encountered in analyzing data from a large and well-documented sample of DWI offenders who were screened, triaged, and tracked for 4 years via driving records. Our hope was to find a method that would allow us to predict which offenders were more likely to reoffend.

2. Methods

Individuals convicted of a first DWI offense in Bernalillo County, New Mexico, were routinely mandated to

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undergo screening at the Lovelace Comprehensive Screening Program (LCSP) in order to determine whether they should be referred to treatment for alcohol- and drug-related problems. The screening process included questionnaires, a computer-based interview, and structured in-person interviews by a counselor with the offender and with a spouse, friend, or relative (Lapham et al., 1995). This assessment provided the basis for a diagnosis of alcohol abuse or dependence, and the client was either referred to treatment or dismissed.

2.1. The sample

The study population was drawn from 4,993 convicted DWI offenders who were referred to the LCSP following a drunk-driving conviction between April 1989 and March 1991. The New Mexico Traffic Safety Bureau maintains a state-wide computerized citation tracking file (CTF) with records of all citations issued in New Mexico. The CTF provided data from two systems: DWI arrests and traffic convictions for moving violations (citations). The LCSP database was matched to the CTF using client identifying information. Matching was not successful for 298 persons. Of the remaining 4695, 74% completed the screening program and were eligible for inclusion in the study sample. Eliminated from the matched data set were 597 who had missing identifier information, MMPI-2, or demographic variables needed for analyses, 780 who were not administered AUI, 509 persons who had an invalid MMPI-2 or AUI, 48 persons of other than non-Hispanic white, Hispanic, or American Indian ethnicity, and 47 persons who lived out-of-state (Table 1). The final sample consisted of 1,496 convicted DWI offenders, with an average age of 31, of whom 77% were male, 49% non-Hispanic white, 42% Hispanic, 8% American Indian, 77% not married, and 86% had at least 12 years of education.

Although a large percentage of the sample was lost due to missing data, our previous studies have demonstrated overall similarity between the LCSP completers and non-completers. Chang, Lapham, and Barton (1996) compared 1,405 clients with incomplete information to 5,154 clients who completed the screening program and found no differences in ethnicity, gender, age, marital status, or years of education between these groups. Another previous study of this sample compared 4-year recidivism rates between subgroups of clients who had a valid MMPI (N = 1,069; L raw score was 8 or below, and the K t-score was 70 or below) and subjects whose MMPI was not valid (N = 315) (Lapham, Skipper, & Simpson, 1997). There were no differences in recidivism rates for these groups.

Table 1
Study population, elimination criteria, and final sample

Convicted DWI offenders court-mandated to the LCSP	*4,993*
Matched to the citation tracking file (94%)	4,695
Subjects eliminated from the matched data set	
Waived from screening by the court system	− 332
No initial contact with the LCSP	− 629
Did not complete screening	− 257
Missing identifier information, MMPI-2, or essential demographic variables	− 597
Missing the AUI	− 780
Invalid AUI profiles	− 22
Invalid MMPI-2 profiles	− 481
Invalid MMPI-2 and AUI profiles	− 6
Other race/ethnicity	− 48
Living out-of-state	*− 47*
Final sample	1,496

2.2. Materials

The AUI (Horn, Wanberg, & Foster, 1990) is a 228-item self-report instrument that assesses alcohol-related problems. It has been lauded as the strongest comprehensive paper-and-pencil instrument for evaluating alcohol problems (Miller, Westerberg, & Waldron, 1995). Besides its 17 primary scales, there are six secondary factor scales, and one third-order scale. The primary scales measure alcohol-related problems across four domains: benefits, styles, consequences, and concerns of alcohol use. Second-level scales combine the primary scales into six more general factors: 1) Enhanced scale; 2) Obsessed scale; 3) Life Disrupt (overt) scale; 4) Life Disrupt (subtle) scale; 5) Anxious-concern scale; and 6) Receptive-awareness scale. The third-level scale is a single scale of overall severity of alcohol involvement (broad involvement). Only second- and third-level scales were used as predictors. For the present study, the AUI was considered valid if the absolute difference between the decile ranks on the overt vs. subtle scales of Life Disruption was less than 3 (Horn et al., 1990). A discrepancy between decile ranks as large as 3 may indicate that the responder is motivated to underestimate the seriousness of his or her involvement with alcohol, or that the responder is answering in a haphazard fashion.

The MMPI is the most frequently used personality instrument in the United States (Whitworth & McBlaine, 1993) and other countries (Dana, 1995). Standardization of the MMPI on the majority population raised concerns around its validity for use with minority populations (Pollack & Shore, 1980; Hoffmann, Dana, & Bolton, 1985). Restandardization of the MMPI in 1989 included black Americans, Hispanic Americans, American Indians, and Asian Americans in the normative sample (Greene, 1991) and produced the 567-item MMPI-2 (Butcher, Dahlstrom, Graham, Tellegen, & Kaemmer, 1989). LCSP converted from MMPI to MMPI-2 during its first year of operation. An MMPI-2 profile was considered valid if the L raw score was 8 or below and the K t-score was 70 or below (Butcher, 1990). Based on previous findings with regard to personality and DWI (Zelhart, 1972; Mozdzierz, Macchitelli, Planek, & Lottman, 1975; Selzer & Barton, 1977; Selzer, 1961), we selected four content scales (Anger, Antisocial

Practices, Depression, and Low Self-esteem) and the MacAndrew alcoholism scale (MAC) (Schwartz & Graham, 1979) as predictor variables.

In addition to the standardized assessment scores, other predictors known to be associated with recidivism were included in the analysis. Age, gender, education, race/ethnicity, arrest blood alcohol concentration (BAC), and prior DWI all have been reported as predictors of DWI recidivism risk (Arstein-Kerslake & Peck, 1985; Bailey & Winkel, 1981; Chang, Lapham, & Wanberg, 2001; Ellingstad, 1974; Hedlund, 1994; Lapham et al., 1997; Moskowitz, Walker, & Gomberg, 1979; Peck et al., 1994; Ross, Howard, Ganikos & Taylor, 1991). Marital status is also included as a variable in the analysis. One previous study in this population found that married offenders were rearrested at lower rates compared to unmarried offenders. In that study, marital status is significant as a univariate predictor but is not significant in a multivariate model (Lapham, Skipper, Hunt, & Chang, 2000).

Individuals with more severe alcohol problems also are more likely to reoffend (Perrine, 1990; Bailey & Winkel, 1981). One indicator of drinking severity is a high arrest BAC (Simpson & Mayhew, 1991; Jonah & Wilson, 1986; Vingilis, 1983). BAC at arrest was known for most offenders referred to LCSP. The judgment of LCSP counselors as to whether the client needed treatment was also tested as a predictor. Treatment compliance has been found to be inversely related to DWI recidivism (Arstein-Kerslake & Peck, 1985; Peck et al., 1994). Noncompliance in this study was reported to LCSP by treatment programs and is defined as missed or canceled screening or treatment appointments, or nonpayment of fees. Finally, LCSP counselors were asked to rate each client, based on all available information and clinical judgment, for risk of DWI recidivism.

Information from the CTF database (which extends back to 1984) was used to determine whether each client had been convicted of DWI or any moving violation citations prior to the date of referral to the LCSP, and for 4 years after the index date on which they entered screening.

3. Results

An overall description of the study sample (Table 1) is followed by a description of differences between nonrepeat offenders (NROs) and repeat offenders (ROs) (Table 2). A *t*-test of mean differences between groups on age was significant (t = 3.80, $p < .01$), with ROs being younger than NROs. A chi-square analysis determined significant differences between NROs and ROs on four demographic characteristics: NROs were more likely to be married; better educated; there were more females in this group; and there were more non-Hispanic whites in this group. Chi-square analysis revealed that neither NROs nor ROs were overrepresented among offenders with invalid MMPI-2 (χ^2 = 0.59 $p > .05$) or invalid AUI profiles (χ^2 = 1.60 $p > .05$).

Table 2
Demographic comparisons between those who were and were not rearrested for DWI in the follow-up period

Demographic variables	NROs (N = 1126)		ROs (N = 370)	
	Mean	*S.D.*	Mean	*S.D.*
Age**	31.41	10.30	29.28	9.02
	N	%	*N*	%
Gender*				
Males	851	76%	302	82%
Females	275	24%	68	18%
Marital status**				
Not married	848	75%	305	82%
Married	278	25%	65	18%
Education**				
Less than 12 years	144	13%	74	20%
12 years	485	43%	171	46%
More than 12 years	497	44%	125	34%
Race/ethnicity**				
Non-Hispanic white	588	52%	149	40%
Hispanic American	452	40%	183	50%
American Indian	86	8%	38	10%

* $p < 0.05$.
** $p < 0.01$.

3.1. Predicting recidivism

The ability to discriminate ROs from NROs based on information gathered at screening was assessed using sequential logistic regression (Table 3). Using a conventional multivariate approach, a model was developed to determine the variables that best predict DWI recidivism. The Wald test was used to evaluate the contribution of an individual predictor to the model. When a discrete predictor has more than two levels, the Wald test estimates the reliability of each degree of freedom separately, but not a discrete predictor as a whole (Tabachnick & Fidell, 1996). The cutoff criterion was set at 0.25. Demographics, offense data (BAC at arrest and number of prior DWI arrests), AUI scores, personality variables (MMPI), referral status, and counselor's judgment of risk were entered into the model as blocks, in a sequential hierarchical structure.

The prediction of recidivism was significantly improved by entry of the five demographic variables, the three prior offense variables, the seven drinking variables, and the two referral status variables (Table 3). Neither the five personality variables (from MMPI) nor counselor prediction of recidivism significantly improved the model. The final model had a sensitivity (proportion rearrested who have a positive test) of 62% and a specificity (proportion not rearrested with a negative test) of 65%, with an overall percent correct classification of 64%. In the test of univariate contribution of individual variables to the model, the predictor's age, gender, marital status, education, race/ethnicity, BAC at arrest, prior DWIs, and referral to treatment were reliably associated with recidivism. When models were computed for males and

Table 3
Sequential logistic regression analysis to predict recidivism (cut value is 0.25)

	Odds Ratio	Correct classification NROs	ROs
Demographic variables**		56.99%	56.69%
Age*	0.985		
Gender*	1.459		
Marital status*	1.480		
Education			
Education (1)	1.272		
Education (2)**	1.885		
Race/ethnicity			
Race/ethnicity (1)*	1.363		
Race/ethnicity (2)	1.277		
Offense data**		61.78%	56.69%
BAC at arrest*	1.357		
No. of prior DWIs*	1.361		
No. of prior citations	1.026		
Drinking data**		63.79%	61.92%
Enhanced	1.044		
Obsessed	0.944		
Life disrupt (overt)	1.055		
Life disrupt (subtle)	1.053		
Anxious concern	1.069		
Awareness	1.022		
Broad involvement	0.950		
Personality		64.66%	60.47%
MAC	1.009		
Anger	0.994		
Antisocial practices	1.007		
Depression	1.008		
Low self-esteem	0.979		
Referral status**		65.33%	63.08%
Treatment**	1.759		
Compliance	1.235		
Counselor's risk estimate		64.75%	62.50%
Risk for recidivism	0.814		

Coding for discrete variables with reference group coded 0:
Gender = female (0); male (1)
Marital status = married (0); not married (1)
Education = > 12 years (0); 12 years (1); < 12 years (2)
Race/ethnicity = non-Hispanic white (0); Hispanic (1); American Indian (2)
BAC at arrest = < 200 mg/dL (0); $\geq$ 200 mg/dL (1)
Treatment = not referred (0); referred (1)
Compliance = no missed appointments/payments (0); missed appointments/nonpayment (1).
* $p < 0.05$.
** $p < 0.01$.

females separately, the above findings held for males; for females, only the demographic variables contributed significantly to the prediction of recidivism.

These analyses were followed with forward stepwise logistic regression to determine which variables accounted for most of the variance when order of entry is not dictated. Variables remaining in the equation at the end of this analysis were age, education, arrest BAC, prior DWIs, the receptive-awareness scale from the AUI, and the MAC raw score from the MMPI-2. Sensitivity was 57%, specificity was 65%, and the overall percent correct was 63%.

3.2. A multiple risk factor approach

A few predictor variables turned up again and again in our equations. We therefore searched for a way in which these more consistent predictor variables might be used to examine prediction in a way that would be readily comprehensible and applicable for clinicians.

The World Health Organization, in its quest for recommended guidelines for safe drinking, took the interesting and simple strategy of examining the continuous distribution of alcohol consumption plotted against various adverse outcomes (Saunders & Aasland, 1987). The basic approach was to examine the distribution looking for a place where risk level seems to turn upward. We reasoned this could be done with each predictor variable, looking for a point in the distribution where actual probability of recidivism rises above the base rate for the sample. Each predictor variable can in this manner be converted into a dichotomous risk factor that is present or absent for a particular individual at any given time.

To determine the independence of these six predictors, a correlation matrix was developed. This indicates generally low correlations among the variables (Table 4). Then, graphic displays of these variables with recidivism were computed using receiver operating characteristic (ROC) curves (SAS Institute Inc., 1995). ROC curves provide a measure of sensitivity and specificity – for those with high predictive accuracy, the curve rises quickly. Variables were individually plotted against recidivism. Each ROC curve, however, rose slowly, indicating low predictive accuracy. The shape of the graph did not give an indication of an optimal cut-point.

Since the ROC curve analysis indicated no specific cut-off points, we recoded these six variables into dichotomous markers (low risk, high risk) based on the point where the recidivism base rate of 25% was exceeded or where the data shifted substantially. The cut-off points for high risk were below 29 years of age, based on 31% of 28 year-olds vs. 18% of 29 year-olds reoffending; less than 12 years of education because in the logistic regression, the reference group was greater than 12 years of education, and 12 years of education was not significantly different from the reference group; arrest BAC of 200 or higher (already dichotomous); at least 1 prior DWI arrest; a raw score of 7 or higher on the AUI receptive-awareness scale based on 26% of those with a raw score of 6 vs. 30% of those with a raw score of 7 reoffending; and a MAC raw score of 23 or higher, based on 17% of those with a MAC raw score of 22 vs. 29% of those with a MAC raw score of 23 reoffending.

As the number of predictor variables in use increases, so does the number of possible combinations of binary scores.

Table 4
Pearson correlations $N = 1496$

	Age	Arrest BAC	Education	Receptive Awareness Scale	MacAndrew Scale
Age					
Arrest BAC	.065*				
Education	– .010	– .012			
Receptive Awareness Scale	.038	.091**	.089**		
MacAndrew Scale	– .091**	.034	.194**	.204**	
Prior DWIs	– .009	.104**	.080**	.127**	.093**

* $p < 0.05$ (2-tailed).
** $p < 0.01$ (2-tailed).

For example, with five predictors, there are 32 possible combinations, and with six predictors, there are 64 possible combinations. Additionally, the number of individuals in the dataset matching each specific profile is reduced, decreasing the accuracy of prediction. In the interest of developing a succinct and easy-to-use table, each possible combination of five of the six variables was analyzed to determine the most effective combination. Each set of five dichotomous variables was entered in a logistic regression, and the resulting regression coefficients were used in the following formula to predict the probability of rearrest for that combination of variables:

$$\text{Probability of recidivism} = \frac{e^{\propto+\beta 1}}{1 + e^{\propto+\beta 1}}$$

Next, we determined the correlation between predicted probability and actual recidivism for each combination of these five variables. These correlations ranged from 0.49 to 0.64. The best combination of five variables (excluding prior known arrests) was age, education, arrest BAC, the receptive-awareness scale from the AUI, and the MAC from the MMPI-2.

Finally, a probability of recidivism table was developed for each risk profile. Included in this table were the actual percentages of individuals with each particular profile who had another DWI arrest within the subsequent 4-year follow-up period. Some profiles had only a few subjects, and the predicted probabilities for them tended to be most discordant from the actual recidivism percentages. The correlation between predicted probability and actual recidivism was $r = 0.64$, $p < .001$ ($N = 32$). Discarding the six profiles for which we had fewer than 10 subjects resulted in a correlation between predicted probability and actual recidivism of $r = 0.85$, $p < .001$ ($N = 26$).

As a general pattern, the greater the number of endorsements on these high-risk variables, the greater the probability of recidivism. Given this trend, one way to simplify the prediction of recidivism is to use the number of risk factors (0 through 5) present in each case. Table 5 shows the actual and predicted probability of recidivism based on the number of risk factors present. Predicted probabilities closely

Table 5
Predicted probability of recidivism based on number of risk factors present ($N = 1496$)

	Probability of repeat offense			
# Risk factors	Predicted	Actual	Error	*N*
0	11%	15%	– 4%	137
1	16%	14%	+ 2%	368
2	23%	25%	– 2%	513
3	32%	31%	+ 1%	352
4	42%	46%	– 4%	109
5	53%	59%	– 6%	17

	Probabilities when including prior arrests:							
	If no prior DWI arrests				If one or more prior DWI arrests			
# Risk factors	Predicted	Actual	Error	*N*	Predicted	Actual	Error	*N*
0	11%	13%	– 2%	123	17%	29%	– 12%	14
1	15%	13%	+ 2%	329	24%	20%	+ 4%	39
2	22%	22%	– 0%	418	32%	37%	– 5%	95
3	30%	29%	+ 1%	253	41%	35%	+ 6%	99
4	39%	44%	– 5%	71	52%	50%	+ 2%	38
5	50%	55%	– 5%	11	62%	67%	– 5%	6

Risk factors are: age < 29; years of education completed < 12; arrest BAC ≥ 200; AUI receptive-awareness scale raw score ≥ 7; and MAC scale raw score ≥ 23.

Table 6
Predictive ability of the models tested in determining rearrest

	Sensitivity	Specificity	Overall % correct	PPV	NPV
Sequential logistic reg. Full model N = 1388 Cutoff = 0.25	62.5%	64.7%	64.2%	36.9%	84.0%
Stepwise logistic reg. Full model N = 1388 Cutoff = 0.25	57.3%	65.1%	63.2%	35.1%	82.2%
Logistic regression 5 Dichotomized variables N = 1496 Cutoff = 0.25	53.5%	65.9%	62.8%	34.0%	81.2%
Probability formula 5 Dichotomized variables N = 1496 Cutoff = 3 +	45.7%	72.6%		35.6%	80.3%
Probability formula 5 Dichotomized variables N = 1496 Cutoff = 2 +	80.5%	61.5%		30.2%	85.7%
Hold-out sample logistic regression 5 Dichotomized variables N = 509 Cutoff = 0.25	60.9%	53.6%	55.6%	32.8%	78.7%
Hold-out sample probability formula 5 Dichotomized variables N = 509 Cutoff = 3 +	38.4%	72.5%		34.2%	76.0%
Hold-out sample probability formula 5 Dichotomized variables N = 509 Cutoff = 2 +	71.7%	42.3%		31.6%	80.1%

PPV = positive predictive value; NPV = negative predictive value

tracked actual repeat offense rates. Sensitivity and specificity, based on the probability formula and using a cutoff of 3+ risk factors, is 46% and 73%, respectively. Lowering the cutoff to 2+ risk factors gives a sensitivity of 81%, and specificity is 61% (Table 6). For comparison purposes, the lower portion of Table 5 shows the actual and predicted probability of recidivism based on the number of risk factors (0 through 5) in conjunction with the sixth risk variable (prior offense).

Comparison of the sequential logistic regression full model with the probability formula presents some problems because the models have different Ns and different number of variables. Therefore, we ran the logistic regression analyses using the same five dichotomized variables with a cutoff criterion of 0.25, and an N = 1496. Results of this model indicate that sensitivity is 53% and specificity is 66% (Table 6).

An important concern, of course, is the extent to which this algorithm would work with offenders other than the group from which it was derived. As a conservative test, we applied the same algorithm with the 509 participants whose MMPI or AUI profiles were judged to be invalid. Two of the markers (AUI Receptive-Awareness, and MMPI MAC scale) were derived from these instruments. If these respondents were falsifying their information, one would expect the algorithm not to work. In fact, as shown in Table 7, predicted reoffense rates again closely mirrored actual recidivism. Paralleling an above-reported analysis, when profiles with fewer than 10 cases were removed from the 32-line source table (N = 17), the correlation between actual and predicted recidivism rates was r = 0.695, p = .002 (Table 7). Using a similar decision rule for classifying individuals in the hold-out sample — e.g., a cutoff score of 3+ risk factors resulted in 38% sensitivity and 72% specificity (Table 6). Again, changing the cutoff score to 2+ risk factors gave a sensitivity of 72% and a specificity of 42%.

Table 7
Predicted probability of recidivism based on number of risk factors present among individuals with invalid response profiles (N = 509)

	Probability of repeat offense			
# Risk factors	Predicted	actual	error	N
0	18%	21%	− 3%	56
1	22%	19%	+ 3%	140
2	28%	29%	− 1%	158
3	33%	33%	0%	119
4	38%	39%	− 1%	31
5	42%	40%	+ 2%	5

4. Discussion

The drinking drivers in this study were very similar in demographics to other DWI populations described, e.g., a young, unmarried, male, with a high school education or less (Moskowitz, Walker, & Gomberg, 1979; Donovan, Marlatt, & Salzberg, 1983; Simpson & Mayhew, 1991; Hedlund, 1994), albeit more ethnically diverse than many samples, with 42% Hispanics and 8% American Indians. Findings of our initial analyses also resembled those of other reports, in that our regression equation to predict recidivism was significantly better than chance. If sample size is large enough, almost any difference between models is likely to be statistically significant (Tabachnick & Fidell, 1996).

A multiple risk factors approach aimed at assessing risk based on number of risk factors produced predicted risk rates that closely paralleled actual reoffense rates during the 4 years after assessment. Among those with 5 risk factors twice as many offenders are arrested, compared with the base rate. However, even for those with no risk factors, 15% were rearrested at a difference of only 10% from the base rate. This might be anticipated from examination of the ROC curve analysis, which demonstrates that the variables used to predict recidivism are not strong predictors. Also, while logistic regression is especially useful when the distribution of responses on the dependent variable is nonlinear, the relationships between the variables under study and recidivism are relatively linear.

In terms of predicting recidivism based on screening, sensitivity describes the ability of the screening test to detect who will reoffend. As the sensitivity of the test decreases, fewer people who will reoffend will be detected by the screening test. Specificity relates to the percentage of people who will not reoffend who test negative on the screening test. As the specificity of the test decreases, an increasing number of people who will not reoffend are falsely labeled as reoffending. In terms of a public health perspective, higher sensitivity would mean that offenders determined to reoffend would likely receive an appropriate intervention (treatment). The probability formula with a cutoff of 2+ had the highest sensitivity rate (81%). The base recidivism rate is 25%. In this population, this means that a wide net would be cast to include a high percentage of those who will reoffend along with a substantial number of those not likely to reoffend (and who would probably be sent to treatment). This strategy is suggested for two reasons. First, there is strong evidence that a high percentage of DWI offenders are alcohol dependent (Lapham et al., 2001) and, therefore, may benefit from treatment. Second, many of these offenders, though not rearrested, may continue to drive drunk. Evidence suggests that only a small percentage of drunk drivers are arrested (Borkenstein, Crowther, Shumate, Ziel, & Zylman, 1964).

Some common limitations are apparent: we could track only in-state ROs, individuals were mandated by the court to screening and perhaps were motivated to minimize problem status, and many individuals did not complete the screening process. As already mentioned, recidivism measures only those offenders who are caught drinking and driving. Arrests may significantly underestimate actual offenders. The predictive generalizability of this particular set of risk factors to other populations remains to be determined; we intend this to be more of a demonstration of an analytic approach that can be used within a particular population to generate an easy-to-use and practical algorithm for predicting recidivism risk. Consistent with many prior findings (Wiggins, 1973), clinical judgment (i.e., of need for treatment, or probability of reoffense) added nothing to our model. Prediction was possible from a simple combination of predictors. This method of unit weighting is robust for making predictions and outperforming clinical intuition (Dawes, 1979). Although the specific predictors may differ from one population to another, the method may be useful for developing a population-specific algorithm. Indeed, for purposes of local prediction, that is precisely what legal authorities are likely to desire.

One concern with this approach is its potential for capitalization on chance, in that the predictor variables were selected from the sample based on stepwise regression. We believe that several considerations diminish this concern, although cross-validation of the method is clearly warranted. First, the specific variables selected by our analysis (except the AUI receptive-awareness scale) have been predictors of DWI recidivism (e.g., Ellingstad, 1974; Moskowitz et al., 1979; Hedlund, 1994; Arstein-Kerslake & Peck, 1985; Bailey & Winkel, 1981; Peck et al., 1994; Lapham et al., 1997). Second, the regression was used only to identify candidate variables but not cut-off scores for risk factors. For the latter we used the pragmatic approach of identifying the score at which recidivism rose above base rate. Third, when we applied the algorithm with a new sample, those whose MMPI or AUI profiles had been judged to be invalid predicted recidivism rates again closely approximated actual rates of repeated DWI in the subsequent 4 years.

The utility of such a table is in the ability to quickly group offenders, based on a few relatively simple variables, into categories of persons likely to repeat the DWI offense. Two instruments are required: the AUI and the 49-item MAC scale from the MMPI-2, taking approximately 60–90 minutes to complete. This method could be applied to determine that DWI offenders warrant special intervention if their predicted risk of recidivism exceeds base rate (in this sample, 25%) by a predetermined margin. From both Tables 5 and 7, for example, one might regard intervention to be warranted when three or more risk factors are present (32–53% predicted recidivism). In this specific table, it is also the case that within this range of ≥ 3, the algorithm is quite unlikely to overestimate the probability of recidivism (maximum error value = +1% among first offenders), giving the offender "the benefit of the doubt."

Of those with 3+ risk factors, 36% will reoffend. The trade-off between sensitivity and specificity would need to be based on reasonable public safety measures. More specifically, correctly classifying over one-third of the ROs (while incorrectly classifying 20% of the NROs) allows programs to offer more intensive services to those most likely to reoffend. To correctly classify a higher percentage of recidivists, one could use a cut point of 2 or more risk factors. This would result in an 80% sensitivity, and would miss only 20% of the recidivists, but the specificity would be low (61%), resulting in almost one-third of the nonrecidivists being misclassified.

Cross-validation is of obvious importance to confirm and improve such an algorithm within a population, or to transport it across populations. The method can be used, of course, with different sets of predictor variables. It is also feasible to include a larger number of predictor variables if sample size warrants. Although the single-profile look-up table becomes unwieldy beyond five predictors, a larger number of variables can be more easily used in a decision table based on the number of positive risk factors (e.g., Table 5). Given the highly questionable value of clinical judgment in predicting recidivism, we believe that the use of such an actuarial approach provides a fairer (and less costly) method for making decisions about court-mandated interventions to reduce repeat offenses. However, some recidivists will still be missed with this approach.

Finally, we note that determining the most effective response at each risk level (e.g., what risk categories respond best to which interventions) is a separate matter. One cannot assume that individuals at higher risk will necessarily respond to interventions intended to reduce risk, and the demonstration of efficacy requires a different line of investigation.

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