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Facilitating targeted intervention in substance abuse treatment programs via a risk scoring methodology

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FACILITATING TARGETED INTERVENTION IN SUBSTANCE ABUSE TREATMENT PROGRAMS VIA A RISK SCORING METHODOLOGY

by

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April 2014

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To facilitate targeted intervention in substance abuse treatment programs, a scoring methodology is developed to identify clients at risk of premature program exit. Designed to be simple enough for a clinician to easily apply in practice, the risk score is derived from self-reported and observable client characteristics collected at program intake. Our motivating problem is improving a residential substance abuse treatment program for military veterans, and we demonstrate the risk score applied to data from 680 veterans who exited from a San Diego-based rehabilitation program from 2009 to 2011. For this program, the existence of a mental health condition, chronic physical health condition, and the client's residence prior to program admission were predictive of successfully completing 150 days of treatment. Length of stay and residence prior to program admission were predictive of successful program completion. The risk score methodology is generalizable and can be customized for any treatment program.

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1. INTRODUCTION

The Veteran's Administration (VA) recently estimated the number of homeless veterans to be between 50,000 and 60,000 (Shane, 2012). Drymalski (2010) and Balshem, Christensen, and Tuepker (2011) review the literature on the rates of substance abuse among the homeless, where studies from the early 1990s through 2004 of various groups of homeless find rates of substance abuse/dependence from just over 50 percent to as high as 80 percent. For example, Balshem et al. (2011, p. 3) cite a survey of randomly selected homeless adults in Pittsburgh and Philadelphia that found "61.4 percent reported psychiatric problems, 79.5 percent reported alcohol or drug abuse or dependence, and 66.1 percent reported having at least one chronic medical condition." Caton et al. (2005, p. 1753) state, "Substance abuse ranks high among factors that distinguish homeless people from those who have never been homeless."

An important question is how to break the cycle of substance abuse that often leads to veteran homelessness. There are a variety of treatment models and methods and, as discussed in Section 1.1, the literature shows that individuals respond differentially. Furthermore, every program is resource constrained and must make resource allocation decisions and choices, so a relevant, programmatic issue is how to best apply those resources in order to maximize the likelihood of successful treatment outcomes. Our motivating problem is assisting an elective, residential, substance abuse treatment program for homeless veterans in the San Diego region. In particular, how might information collected from clients at the time of admission to a treatment program be used to improve the efficacy of the program?

1.1 LITERATURE REVIEW

There are numerous prior studies of predictors of retention in substance abuse treatment programs, but fewer on retaining homeless people in substance abuse programs, and fewer still on retaining homeless military veterans. In a review of the literature on homelessness among military veterans, Balshen et al. (2011; see Figure 1 therein) propose a conceptual model of risk factors for homelessness. They posit that these risk factors are a result of early life exposures and veteran-unique exposures, where early life exposures include psychiatric illness, abuse, family dysfunction, and foster/institutional care, and where veteran-unique exposures include physical/cognitive disabilities, post-traumatic stress disorder (PTSD)/depression/anxiety, and alcohol/drug abuse. Retention is generally considered a critical factor to successful treatment outcomes. In a synthesis of the literature on substance abuse treatment for the homeless, Zerger (2002, p. 4) says,

> One of the most consistent findings in this research is the direct association between the length of time spent in treatment and positive outcomes. Yet the challenge of retaining clients in substance abuse treatment is intensified when the target population is homeless: drop-out rates of two-thirds or more are common.

In terms of homeless veterans with substance abuse problems, the most relevant studies are Sussner et al. (2008); Justus, Burling, and Weingardt (2006); Stack et al. (2000); and Wenzel et al. (1995). Sussner et al. (2008, p. 345), in an evaluation of 197 homeless veterans enrolled in a residential care program of the VA New Jersey Health Care System, find that

> Self-reported alcohol use severity, diagnosis of an antisocial behavior disorder, and self-reported days since last use of drugs or alcohol were significant independent predictors of type of discharge. . . . The severity of depressive symptoms and the number of lifetime psychiatric hospitalizations was not associated with the likelihood of premature discharge.

In a study of 596 veterans admitted to a Palo Alto, California residential substance abuse treatment facility, Justus et al. (2006) find that clients who are younger, female, and have a depressive disorder had the highest rates of treatment program completion. Conversely, a current personality disorder and a history of psychiatric disorder were associated with poorer rates of retention and program completion. Stack et al. (2000) retrospectively analyzed 340 veterans admitted to a 120-day substance abuse treatment program. They found that White patients were less likely to complete residential substance abuse treatment in a program in which the majority of both therapists and patients were Black. Younger Black veterans and those with back pain were also less likely to complete treatment. Additionally, Wenzel et al. (1995, p. 245), in a study of 367 homeless male veterans admitted to a residential treatment program at the West Los Angeles VA Medical Center, found that “veterans who were black, who had poor employment histories, or who had problems with alcohol” were associated with premature discharge.

Other recent studies on (nonveteran) homeless populations with substance abuse disorders include Drymalski (2010), Fuller (2010), Thull (2009), Curran et al. (2009), Caton et al. (2005), and King and Canada (2004). As with the studies in the previous paragraph, the specific predictors of treatment success, including demographics, health conditions, and treatments, vary in these studies. As Zerger (2002, p. 5) says, “Many of the results depend, for example, on the client make-up (dually-diagnosed vs. substance-users-only), model of service delivery, availability and access to auxiliary services and staff, and definitional issues (e.g. intensity level of case management).” Zerger (2002, p. 44), however, citing Stahler (1995, pp. xxii-xxiii) goes on to say,

> It appears that there are certain subgroups of clients who will have more positive outcomes than others, most notably those with higher educational attainment, with less severe substance use, less criminal involvement, and those who are less socially isolated. This type of information may be useful for *matching clients to appropriate treatment services*. [Emphasis in the original text.]

As the following quotes demonstrate, this idea of tailoring treatment seems to have started to take root in the literature and, perhaps, in practice. For example, Thull (2009, p. 203) writes:

> Within the behavioral health field as a whole, and in the substance abuse treatment field in particular, there has been increasing pressure to move beyond the mere description and identification of factors that are associated with treatment retention and/or positive treatment outcomes. The focus is slowly shifting to designing, implementing, and evaluating individually-tailored treatment interventions that correspond to the distinct, yet shared, needs of various subgroups of clients (Castel et al., 2006; Mertens & Weisner, 2000; Rapkin & Dumont, 2000; Veach et al., 2000).

Similarly, Sussner et al. (2008, p. 348) say:

> Our team has also begun implementation of a risk stratification initiative in which veterans at heightened vulnerability for premature termination and subsequent problems in the community are provided with enhanced clinical oversight to help them stay on a path toward sustained recovery. To achieve this goal, we have incorporated a modified version of the 'zoning method' of case management to prioritize clients in terms of clinical need (Ryrie & Hellard, 1997). After the initial diagnostic interview shortly after admission, clients are assigned to low, medium, or high risk categories.

1.2 OUR GOAL

This technical report summarizes the results of our research in which we focused on the question asked in the opening section: How might information collected from clients at the time of admission to a substance abuse treatment program be used to improve the efficacy of the program? Specifically, our goal is to facilitate targeted intervention of clients by developing a simple scoring methodology to identify those at greater risk of premature program exit. The risk score is derived from self-reported and observable client characteristics collected at the time of intake into a program. It is designed to be simple enough that a clinician can easily apply it in practice, but is based on rigorous, empirical modeling and is highly correlated to the predicted risk of premature program exit. We demonstrate its application using data from a specific San Diego-based rehabilitation program, though the approach is general enough that it can be applied to and customized for other treatment programs and other client cohorts.

Section 2 describes the San Diego data and how we analyzed it. Section 3 provides the results of our analysis and how we then used the results to develop the risk score. Section 4 is a discussion of our results, including their limitations, and recommendations for future research.

2. MATERIALS AND METHODS

Our work is motivated by the Veteran's Rehabilitation Center (VRC) run by the Veterans Village of San Diego (VVSD). Based on a continuum of care model, VVSD's VRC is an elective, residential, early-treatment program for homeless veterans who have substance abuse issues. The VRC is integrated with structured case management and mental health therapy, and simultaneously addresses addiction, mental health, medical, legal, and employment issues for homeless veterans (VVSD, 2012).

VVSD VRC clients proceed through two broad periods of treatment. The first, which is nominally 150 days in length, consists of an assessment phase and an initial recovery phase (referred to as Phase 0 and Phase 1 in the VRC). During the assessment phase, clients are evaluated and observed to determine precise program needs. Following this, the client enters the initial recovery phase, which has a prescribed structure in which clients are required to attend classes and group meetings that include alcohol and drug education, and a 12-step sequence in both Alcoholics Anonymous and Narcotics Anonymous. We refer to these combined phases as the recovery period. Clients successfully completed the recovery period if their VRC length of stay exceeded 150 days, by which time they must have completed both Phase 0 and Phase 1.

In the second period, which varies in length, clients receive job search and job application skills. During this time, they complete a comprehensive employment course and attend weekly meetings in support of their treatment from the recovery period. Clients seek to secure employment opportunities, continue to work with their sponsors in 12-step recovery, and make final preparations for full reintegration into society. We refer to this as the reintegration period. Clients successfully completed the reintegration period if their record indicated that they either graduated or acquired housing. Otherwise, they did not complete it, prematurely exiting the program for reasons that ranged from severe rule violations to noncompliance with various VVSD policies, including drug and alcohol policies, to missing a bed check. See Coté (2012) for additional details about VVSD, the data, and the treatment program.

2.1 DATA

The data consist of all 680 veterans (57 females, 623 males) who exited VVSD's VRC program between 2009 and 2011. Data include demographics (gender, age, race, ethnicity, education level, veteran status, residence prior to program entry), health status (disabling condition, chronic physical health condition, mental health condition, physical disability, developmental disability, victim of domestic violence), and treatment information (program entry date, program exit date, length of stay, and reason for leaving). The demographic and health status data are client self-reported and were obtained at the time of client VRC program admission via in-person interviews.

Most clients were between the ages of 31 and 58 years (80%; range: 20-81 years old). All had substance abuse problems, which was a criterion for program admittance, and all are veterans. Substances abused include alcohol, soft and hard illegal drugs (e.g., marijuana, hashish, methamphetamines, cocaine, heroin), and over-the-counter and prescription drugs. See Table 1 for population summary statistics of select client characteristics.

Tables 2 and 3 provide the mean length of stay, the percent of clients that completed the recovery period, and the percent that completed both the recovery and reintegration periods, by various demographic characteristics and health conditions. Table 2 shows that there are statistically significant differences in mean length of stay by client combat era, educational level, and by where a client lived prior to admission to VVSD. As shown in Figure 1, combat era is, of course, correlated with age, and Table 2 thus shows that older clients tend to stay in the treatment program longer. Other than client living situation prior to admission to VVSD, there are no differences in terms of completion percentages by client demographics.

Table 1. Selected Client Characteristics (N=680).

Characteristic	Count	Percent
Gender		
Male	623	91.6
Female	57	8.4
Race		
White	466	68.5
Black	176	25.9
Other	38	5.6
Ethnicity		
Hispanic	91	13.4
Non-Hispanic	589	86.6
Combat Era		
Vietnam era and prior	44	6.5
Post-Vietnam era	258	37.9
Persian Gulf era	222	32.7
OEF/OIF era	156	22.9
Education		
Less than high school	24	3.5
High school graduate or GED	440	64.7
Some college or more	54	8.0
Don’t know	162	23.8
Living Situation Prior to Admission		
Homeless	117	17.2
Treatment facility	246	36.2
Temporary housing	94	13.8
Prison/incarceration	90	13.2
Don’t know	133	19.6

Table 2. Length of Stay and Treatment Completion Rates by Demographic Characteristics.

Characteristic	Mean Length of Stay (Standard Error)	Completed Recovery (%)	Completed Recovery & Reintegration (%)
Gender			
Male	207.4 (6.4)	55.9	42.9
Female	210.1 (19.7)	63.2	40.4
F or χ^2 statistic	0.016	1.132	0.134
Race			
White	203.3 (7.3)	55.4	41.4
Black	224.9 (11.9)	60.2	47.7
Other	180.1 (25.4)	52.6	34.2
F or χ^2 statistic	1.789	1.470	3.251
Ethnicity			
Hispanic	180.7 (16.0)	50.5	35.2
Non-Hispanic	211.8 (6.6)	57.4	43.8
F or χ^2 statistic	3.024	1.498	2.405
Combat Era			
Vietnam era and prior	221.3 (25.3)	61.4	50.0
Post-Vietnam era	227.4 (10.4)	59.7	45.3
Persian Gulf era	209.3 (10.6)	56.8	43.7
OEF/OIF era	168.6 (11.0)	49.4	34.6
F or χ^2 statistic	4.674 **	4.733	5.956
Education			
Less than high school	293.5 (31.9)	75.0	66.7
High school graduate or GED	197.7 (7.5)	54.3	40.7
Some college or more	190.2 (20.3)	53.7	38.9
Don’t know	227.7 (12.4)	60.5	45.7
F or χ^2 statistic	4.065 **	5.416	7.277
Living Situation Prior to Admission			
Homeless	213.0 (14.0)	62.4	45.3
Treatment facility	234.6 (10.9)	62.2	48.0
Temporary housing	210.8 (16.7)	52.1	38.3
Prison/incarceration	197.5 (15.9)	53.3	48.9
Don’t know	157.6 (11.2)	45.9	29.3
F or χ^2 statistic	5.357 ***	12.117 *	14.997 **

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

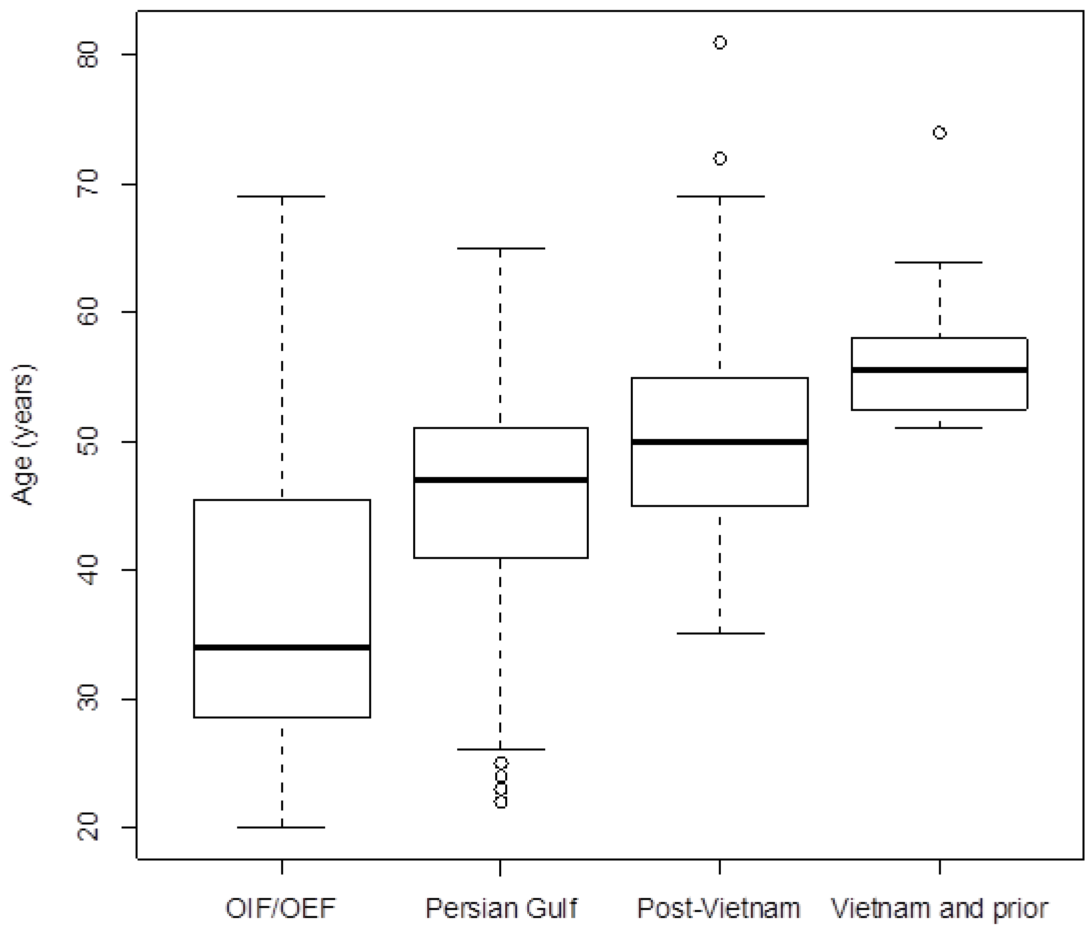

Figure 1. Boxplots of Client Age by Combat Era.

In contrast, Table 3 demonstrates there are differences in mean length of stay by all health conditions (physical, developmental, chronic, and mental). In addition, the fraction completing both the recovery and reintegration periods significantly differ by mental health condition and the fraction completing reintegration also differs by developmental disability category.

Table 3. Length of Stay and Treatment Completion Rates by Health Conditions.

Characteristic	Mean Length of Stay (Standard Error)	Completed Recovery (%)	Completed Recovery & Reintegration (%)
Physical Disability			
Yes (n=107)	244.9 (18.1)	58.9	48.6
No (n=506)	204.6 (6.8)	56.7	40.3
Don't know (n=67)	174.3 (16.7)	50.7	50.7
F or χ^2statistic	4.248 *	1.158	4.470
Developmental Disability			
Yes (n=27)	343.4 (48.5)	66.7	63.0
No (n=585)	205.1 (6.3)	56.6	40.9
Don't know (n=68)	175.5 (16.5)	51.5	50.0
F or χ^2 statistic	11.720 ***	1.836	6.828 *
Chronic Physical Health Condition			
Yes (n=93)	256.5 (18.8)	66.7	49.5
No (n=519)	203.3 (6.8)	55.5	40.5
Don't know (n=68)	173.3 (16.5)	50.0	50.0
F or χ^2 statistic	6.285 **	5.294	4.282
Mental Health Condition			
Yes (n=352)	184.9 (8.4)	48.6	35.2
No (n=294)	235.2 (9.3)	64.6	48.6
Don't know (n=34)	203.7 (22.3)	67.6	67.6
F or χ^2 statistic	8.223 ***	18.599 ***	20.927 ***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Comparing the results of Table 2 to that of Sussner et al. (2008), Justus et al. (2006), Stack et al. (2000), and Wenzel et al. (1995), there are some consistencies and some inconsistencies. The lack of any gender or race/ethnicity differences differs from Justus et al. (2006), Stack et al. (2000), and Wenzel et al. (1995). Similarly, Figure 1 and the combat era results in Table 2 would seem to suggest an inverse relationship between age and length of stay. The correlation, however, is very small (r = 0.002) and statistically insignificant. That, along with the lack of significance between combat era and percent of clients completing recovery and reintegration, is consistent with the results of Justus et al. (2006). Finally, our results for education are the opposite of Zerger (2002), but in our data only 24 of 680 clients have less than a high school education;

when removed from the data, education-based differences are no longer statistically significant (F = 2.383, p-value = 0.09).

In analyses done for each of the years individually (not shown here), we did observe some differences by various demographics. This suggests caution is warranted when analyzing smaller sets of data, where random fluctuations in cohort demographic characteristics may be spuriously associated with the outcome measure of interest. These types of spurious results can also arise when models are overfit, so that the final models reflect the details of a specific set of data rather than the broader population phenomena. For our data, as Section 3 (Results) shows, none of these demographic characteristics were significant in our final models.

Turning to Table 3, the significance of the mental health condition variable, in terms of length of stay and percent of clients completing the recovery and reintegration treatment periods, is consistent with Sussner et al. (2008) and Justus et al. (2006). The significance of physical disability, in terms of length of stay, seems inconsistent with Stack et al.'s (2000) findings about back pain, but our physical disability variable encompasses a wider range of disabilities that are not necessarily associated with pain, so these results may simply be incomparable. Perhaps the most important insight from Table 3 is that, while all four health condition variables are significant in terms of mean length of stay, with the exception of the mental health variable, this generally did not translate into differences in terms of the percent of clients successfully completing the recovery period or the combined recovery and reintegration periods.

2.2 MODELING THE DATA

In order to determine those variables most associated with treatment program outcomes, we fit two logistic regression models to the data. The first models a client prematurely exiting during the recovery period as a function of the client's demographics, health conditions, and treatment information. This model was fit to all 680 clients in the data, of which 384 successfully completed the recovery period and 296 prematurely exited (for a 56% success rate). A second logistic regression model was then fit to those who successfully completed the recovery phase, where the probability of prematurely exiting during the reintegration period was modeled as a function of demographics, health conditions, and treatment information. This second logistic regression model was fit to the 384 clients who successfully completed recovery, of which 266 successfully completed reintegration and 118 prematurely exited (for a 69% conditional success rate).

There are a number of reasons for fitting two separate models. First, the recovery and integration periods are administered as distinctly separate phases by VVSD, so it makes sense from a management point of view to model them separately. Second, successful completion of the recovery period is a prerequisite to entering the reintegration period. Thus, in the aggregate, clients in the reintegration period are fundamentally different than those in the recovery period. Finally, because they are different, there may be completely different phenomena occurring in the two periods and we do not want to confound them in one model.

To ensure that we did not overfit these models, we first used the 2009 and 2010 data to do out-of-sample predictions of the 2011 data. We did this to determine an appropriate significance level for variable selection. This turned out to be 0.02, more conservative than the typical 0.05 significance level, but not quite as conservative as a 0.01 level. Of course, for the final model we used all the data so as not to lose the information in the most recent year of data. We again, however, fit the three-year model using a significance level of 0.02, but now we had some assurance that we were less likely to be overfitting while simultaneously providing a model that should be most effective for 2012 predictions.

Ultimately, the model results were distilled down into a simple risk score that is easy to implement in a clinical setting. The challenge in so doing was to ensure that the score appropriately captured the critical model results, yet was simple enough to apply during the initial diagnostic interview shortly after admission, so that clients could be assigned in real time to an appropriate risk category.

3. RESULTS: DERIVING THE RISK SCORE

Table 4 shows the results of the logistic regression models fit using all three years of data where the dependent variable was an indicator for prematurely exiting either the recovery or reintegration period. For the recovery period model, two health conditions were significant (existence of a mental health condition and existence of a chronic physical health condition), and the client's living situation prior to admittance to VVSD was significant. The presence of a mental health condition contributed to an increased probability of premature program exit while the presence of a chronic physical health condition contributed to a decreased probability of premature exit. In terms of prior living conditions, clients who had been homeless or in a treatment facility (hospital, residential detox center, or residential psychiatric facility) immediately prior to entering VVSD were more likely to successfully complete the recovery period than those who had been in some type of temporary housing (emergency shelter, including hotel or motel paid for with or without emergency shelter voucher; transitional housing for homeless persons; rental housing via VASH housing subsidy; staying or living with family or friend) or who had been incarcerated.

Table 4. Logistic Regression Model Results Estimating Probability of Exit During the Recovery and Reintegration Periods.

Covariate	**Recovery Period**		**Reintegration Period**	
	$\hat{\beta}$	**Odds Ratio**	$\hat{\beta}$	**Odds Ratio**
Health Conditions				
Mental health condition	0.716 ***	2.05		
Chronic physical health condition	–0.596 *	0.55		
Prior Living Situation				
Homeless	–0.487 **	0.61	–0.512	0.60
Treatment facility	–0.487 **	0.61	–0.614	0.54
Temporary housing			–0.039	0.96
Prison/incarceration			–1.308 **	0.27
Length of stay (after recovery period)			–0.008 ***	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The model for premature exit of the reintegration period shows that, consistent with the literature, length of stay is highly significant and the less time that a client is in treatment, the less likely he or she is to successfully complete it. Also significant is client living situation prior to admittance to VVSD. In this phase of treatment, however, conditioning on successful completion of the recovery period, those who had been incarcerated are more likely to successfully complete reintegration compared to those who had been homeless, in a treatment facility, or in temporary housing. On the other hand, as with the recovery period, those who had been in temporary housing were least likely to successfully complete reintegration.

Figure 2 plots the probability of prematurely exiting during the reintegration period as a function of length of stay and living arrangements prior to treatment. This is calculated in the usual way, using the appropriate coefficients from Table 4 and the expression

$$\hat{p} = \frac{\exp\left(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \cdots + \hat{\beta}_k x_k\right)}{1 + \exp\left(\hat{\beta}_0 + \hat{\beta}_1 x_1 + \cdots + \hat{\beta}_k x_k\right)}. \tag{1}$$

As a management tool, Figure 2 nicely communicates the major reintegration period findings. For example, it visually demonstrates the effect of length of stay, where it is evident that someone who is still in the reintegration program after a year is roughly half as likely to prematurely exit as an equivalent person entering reintegration just after completing recovery. It also shows that an individual who came to VVSD from temporary housing is almost twice as likely to prematurely exit during the reintegration period as someone who was incarcerated immediately prior to VVSD.

Recovery period results are not amenable to summary in a simple graphic and, while Equation 1 can still be used to calculate the probability of premature exit, it is unreasonable to expect a clinician to do the necessary calculations. Rather, clinicians need a simple scoring scheme to appropriately classify clients according to risk of premature exit during the recovery period. Furthermore, the scheme must logically classify clients into a reasonably small number of risk groups so that clinicians can both easily keep track of and practically differentiate among the groups.

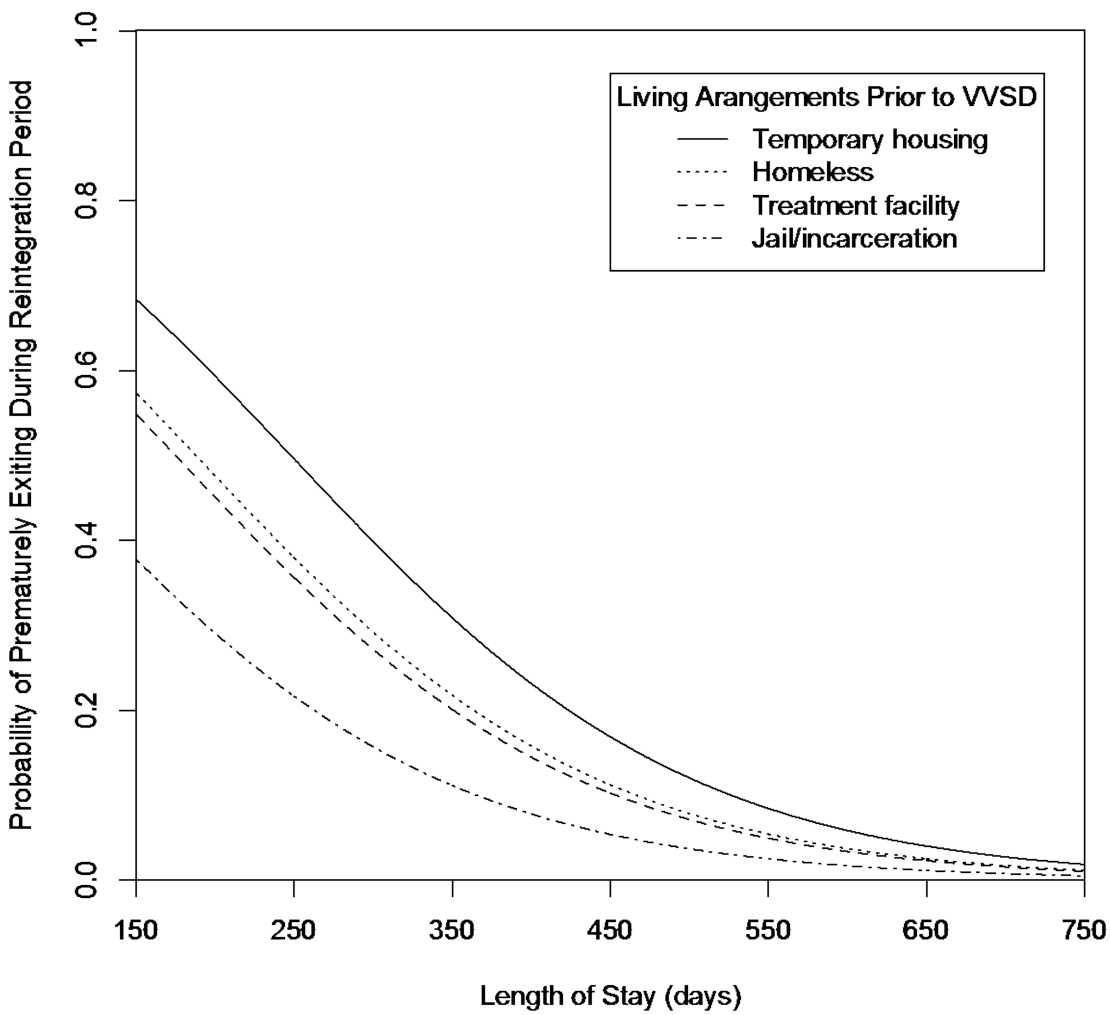

Figure 2. Probability of Prematurely Exiting During Reintegration Period as a Function of Length of Stay and Living Arrangements Prior to Treatment (Conditioned on Successful Recovery Period Treatment Completion).

Per Table 4, there are three significant variables in the recovery model (mental health, chronic physical health, and prior living condition). Had each of the levels of each of the three variables been significantly different, as shown in Tables 2 and 3 that would have resulted in 3 x 3 x 5 = 45 different premature exit probabilities. In this application, however, the mental health and chronic physical health variables reduced to binaries (existence of the condition versus lack of the condition or unknown) and the prior living condition also collapsed into two levels (homeless or treatment facility versus temporary housing, incarceration, or unknown) so that there are only eight probabilities.

From this, we created a simple point scheme that classified clients into one of four premature exit risk categories (very low, low, average, and high), corresponding to 0, 1, 2, or 3 points which are assigned based on client characteristics. Each client initially starts at 2 points, which corresponds to a "baseline" individual:

- who does not have a mental health condition (or whose mental health status is unknown);
- who does not have a chronic physical health condition (or whose physical health status is unknown); and
- whose prior living condition was incarceration, temporary housing, or it is unknown.

Then, if the individual deviates from these conditions, points are either added or subtracted as follows:

- if the individual has a mental health condition, add 1 point;
- if the individual has a chronic physical health condition, subtract 1 point; and,
- if the individual was either homeless or came from a treatment facility prior to VVSD, subtract 1 point.

This simple scoring scheme has a number of advantages. First, it is easy to administer, only requiring the clinician to determine three facts: the client's mental health status, chronic physical health status, and prior living condition. Second, as shown in Figure 3, the scores are highly correlated with the estimated exit probabilities ($r = 0.98$), they appropriately group individuals with similar premature exit probabilities, and point score differences are reasonably consistent with probability differences. Third, as Table 5 demonstrates, the scoring scheme results in four groups that logically correspond to reasonable groupings of exit probabilities, and the fraction of clients who actually prematurely exited in each group is consistent with the probability of exit estimated from the fitted logistic regression model. Finally, as shown in Figure 4, it is simple enough to put on a card that clinicians can carry in a wallet.

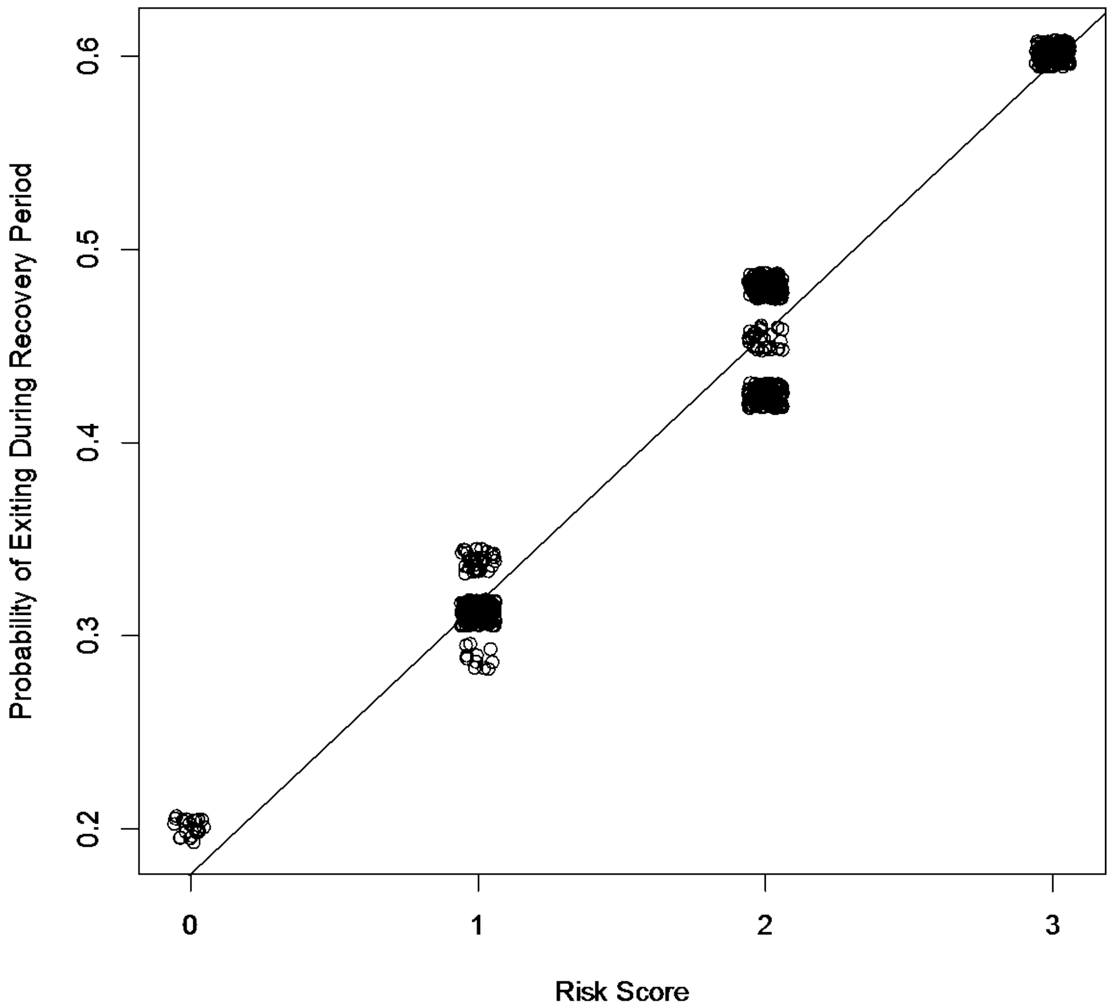

Figure 3. Plot of Estimated Probability of Exiting During Recovery Period vs. Risk Score (r = 0.98). Points Were Jittered to Show the Density of Points for Each Combination of Total Points and Probability of Exiting.

Table 5. Comparison of Logistic Regression Model Estimated Probability of Exiting During Recovery Period vs. Empirical Fraction of Population Who Exited.

Total Points	**0**	**1**	**2**	**3**
Estimated Probability of Exit	0.20	0.29-0.34	0.42-0.48	0.60
Fraction of Clients that Exited	4/22=0.18	62/202=0.31	147/314=0.47	83/142=0.58

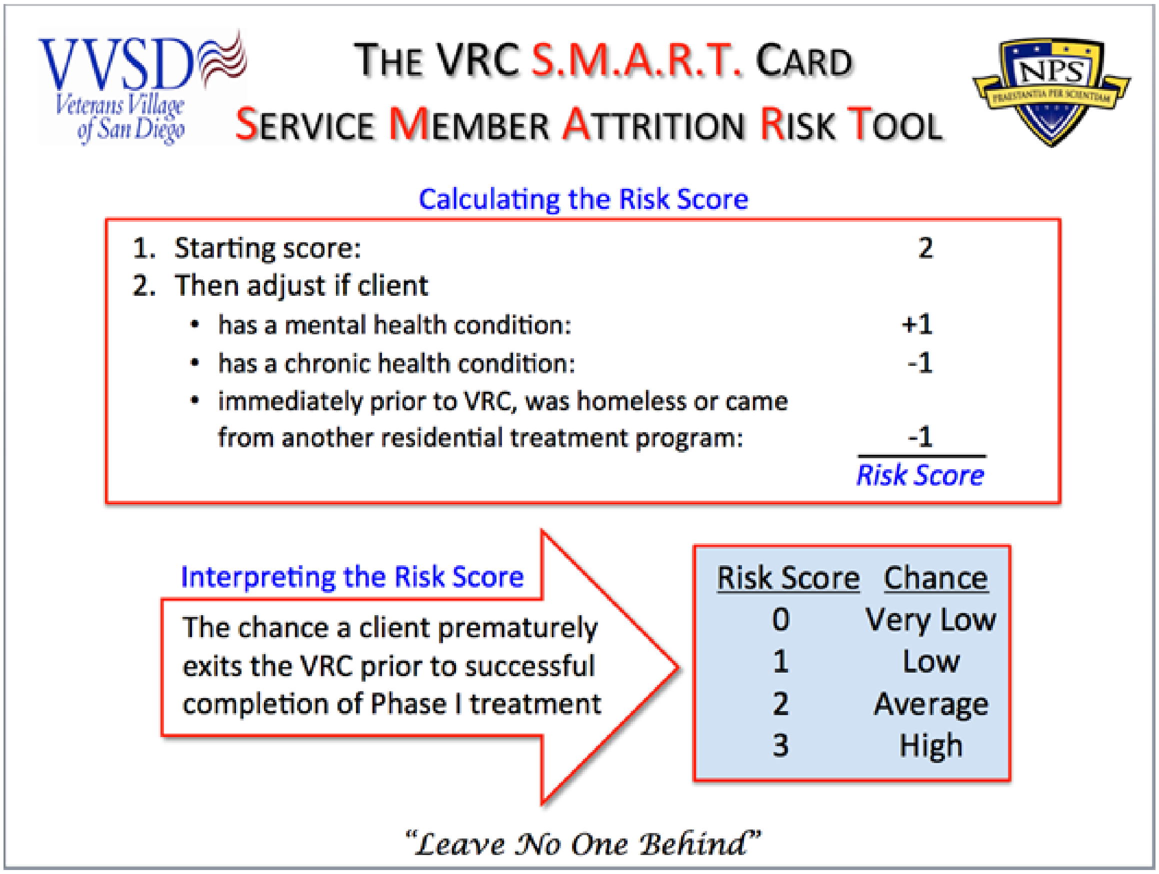

Figure 4. SMART Card.

Note that we purposely set up the scoring scheme to start at 2. First, a risk score of 2 corresponds to the group with a probability of premature exit that is at the average rate for the VRC. So, the point scheme then makes it clear which characteristics are associated with changes from the average. Second, and more importantly, we set it up this way so that evaluators only had to determine the existence of one or more conditions. In particular, we did not want the evaluators to assign points based on not knowing whether a condition existed or not, which was a possible outcome for all of the characteristics in the model. At issue is that we cannot be certain how or why this information is missing and, if evaluators were asked to try to determine or affirm that the information was missing they would likely do so in a way different from how they arose in our data. The result could be a completely different information solicitation dynamic that, in the worst case, could result in incorrect client classifications. In the absence of this complication in other applications, it might be attractive to start the risk score at 0 and then add points corresponding to characteristics associated with increasing risk.

That construction of a simple scoring scheme was possible was not evident to us when we started this research. In fact, because $\hat{p}$ is not a linear function of the independent variables in Equation 1, we certainly did not expect to be able to achieve the high correlation between the point totals and the estimated probabilities. As Figure 3 shows, however, it was possible. In fact, we first found a more complicated scoring scheme that kept all eight groups separate that achieved a correlation of 0.998. We subsequently revised it because the complexity of the point scheme was impractical from an implementation viewpoint and, thus, we traded a bit of analytical precision for easier implementation.

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4. DISCUSSION

Zerger (2002, p. 4) said, “In substance abuse treatment, a gap exists between scientific research and clinical practice that is not common to other fields of medicine.” This technical report is an attempt to help bridge this gap, at least for homeless veterans, in the sense of providing clinicians with a tool that will help them customize interventions. As described in Section 1 (Introduction), using a clustering approach and the application of the Ryrie et al. (1997) zoning method, Thull (2009) and Sussner et al. (2008), respectively, have also made contributions towards bridging this gap for homeless veterans. Our approach differs from standard clustering methods in that the logistic regression model takes into account the risk of premature discharge. Our method may also provide a more quantitatively rigorous foundation for the zoning method.

One caveat is in order, at least for how our method was implemented in this problem. Figure 3 shows that three separate groups with similar premature exit probabilities are grouped together with Risk Score=1 and three other groups with Risk Score=2. Focusing on Risk Score=2, the three clouds of points correspond to the baseline group as previously defined (n = 137); clients with a mental health condition, but who also have a chronic physical health condition (n = 27); and clients with a mental health condition, but who were either homeless prior to admission to the VRC or who came from another treatment program (n = 150). Thus, for example, if part of the tailored intervention focuses only on clients with a mental health condition, then individuals with that particular condition are in both risk score categories (and, in fact, 33 individuals are also in the Risk Score=1 group: those with both a chronic physical health condition and who were either homeless prior to admission to the VRC or who came from another treatment program). The point is that this particular implementation focused on grouping clients based on risk of premature exit, which may or may not result in clinically meaningful groups, and thus may either require further modification or it may require more than four types of targeted interventions.

Furthermore, part of the motivation for this approach was to improve the efficacy of the treatment program, but how to achieve that requires further research. For example, one might assume that program efficacy will be improved by transferring some resources from those with lower risk scores to the group with the highest risk score. Whether that improves the efficacy of the program, however, in the sense of improving the overall success rate of the treatment program, is not clear. It could be that those in the highest risk category require significantly more resources to improve treatment success rates and that the same level of resources applied to one of the lower risk categories could result in a greater overall treatment success rate.

In addition, for all of these approaches some caution is warranted because as soon as the treatment intervention is modified in response to client risk stratification, the models upon which the modification was made begin to become less relevant. The more the intervention is modified, the more the model results will eventually need to be reassessed. Indeed, the insertion of a “feedback loop” from analysis to intervention means that it will be important to periodically redo the analysis and then subsequently update the risk-scoring heuristic as appropriate. Of course, in the context of homeless veterans, and the huge demographic shift underway with the veterans who have returned from Iraq and Afghanistan, continuing reassessment is important anyway. Also, expanding the models to include treatment process variables would likely improve their predictive accuracy.

Returning to the particular results for the population we analyzed, in our final models we found that a client’s mental health condition, physical health condition, and prior living situation were statistically associated with premature exit during the recovery period. Existence of a mental health condition increased the chance of premature exit, while a chronic physical health condition and having either been homeless or in a treatment facility decreased the chance of a premature exit. For the reintegration period, length of stay was highly significant and having been incarcerated just prior to admission was significant. Notably, unlike some previous studies, no demographic variables were significant, and clients that had been in temporary housing prior to admittance were least likely to successfully complete either the recovery or reintegration treatment periods. This latter finding should be noted by advocates and evaluators of the housing-first treatment model (see, for example, Pearson et al., 2007 and Kertesz, et al., 2009), at least as that treatment model relates to the successful treatment of substance abuse.

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