Research and Evaluation

RESEARCH BRIEF

Nature Imagery in Prisons Project at the Oregon Department of Corrections

Director's Office

Oregon Youth Authority

March, 2016

Two analyses were conducted to determine if the Nature Imagery in Prisons Project (NIPP) reduced disciplinary referrals (DR) in the Intensive Management Unit (IMU) at Snake River Correctional Institution, Oregon Department of Corrections. The first analysis showed that IMU E side B (where nature videos were shown during regular exercise times) had much lower (26%) rates of DRs than IMU E side A (where no videos were shown) during the first year following the implementation of the NIPP. The second analysis compared DR rates of inmates on IMU E side B to all other inmates in the IMU system during the first year of implementation and found a nearly statistically significant reduction in DRs (p=.057) after controlling for risk indicators associated high DR rates and inmate cell movement. Collectively, both studies provide evidence that NIPP may be an effective intervention for reducing DRs. Although not definitive, the findings from these studies also support further implementation and investigation of NIPP.

Introduction

The Intensive Management Unit (IMU) at Snake River Correctional Institution (SRCI) houses some of the most difficult to manage inmates in the Oregon Department of Corrections (DOC) prison system. In particular, IMU E houses inmates with behavioral health issues that require constant demand on staff time and resources, causing general disruption to daily living on that unit. High rates of disciplinary referrals (DRs) and cell extractions are a constant challenge for IMU E staff. To address this issue, staff assigned to IMU E started to "think outside of the box" and looked for possible solutions to their problems. After viewing a 2010 Ted Talk given by Biology Professor Nalini Nadkarni, Ph.D. (http://www.ted.com/talks/nalini_nadkarni_life_science_in_prison.html) that described using still pictures of trees in a Washington state IMU, the staff decided to test this novel intervention with this difficult population.

The mission of the Oregon Youth Authority is to protect the public and reduce crime by holding youth offenders accountable and providing opportunities for reformation in safe environments.

Intervention: Nature Imagery in Prison Project

Inmates on IMUs are allowed 45 minutes per day to exercise. Each IMU offers two sets of "indoor" and "outdoor" exercise rooms; one set on each side of the unit. Inmates alternate between the outdoor and indoor exercise rooms, rotating every other day. During their indoor rotation, inmates from IMU E side B were offered the chance to view projected videos of a variety of habitats of "nature.", including forests, oceans, rivers, and deserts. Inmates could choose from 38 projections, with or without sound (some of the videos had classical music and some had the sounds of the nature images), or choose not to have the projector on during their exercise time in the indoor room. This intervention is now referred to as the Nature Imagery in Prisons Project (NIPP).

To investigate whether NIPP was actually reducing problem behavior, Mark Nooth, Superintendent, SRCI contacted the research unit at DOC. At that time, DOC and the Oregon Youth Authority (OYA) had an agreement about sharing research resources, so DOC Research invited OYA Research to conduct a study designed to estimate the effects of NIPP on problem behaviors in the IMU. As a result, staff at SRCI IMU E collaborated with OYA researchers and researchers from the University of Utah, and designed the study to determine if NIPP reduced disciplinary referrals (DRs). This research brief presents that study.

Research Question

Is there a relationship between NIPP participation and reduction in person-day rates of disciplinary referrals (PDRDR)?

Analysis

Two analytical methods estimated the effects of NIPP on disciplinary referrals: (1) Chi-square goodness-of-fit; and (2) Multiple Linear Regression. Both analyses included a risk measure developed using Stochastic Gradient Boosting (SGB; TreeNet in Salford Systems Software; Friedman, 1999), a predictive analytic machine learning algorithm that estimated the risk of high PDRDRs while in the IMU. For Analysis 1 — Chi-square goodness-of-fit analysis — difference scores were calculated in order to test whether the person-day rate of disciplinary referrals (PDRDR) inmates received (describe in detail below) changed in association with the NIPP implementation.

For Analysis 2 — Multiple Linear Regression — the association between PDRDRs and spending at least 30 days in IMU EB during the post period was assessed. The regression estimated the strength of the association between NIPP and PDRDRs while controlling for variables associated with risk of having high PDRDRs while in the IMU. Descriptions of the participants and variables are provided below.

The software packages used for the risk model, Analysis 1, and Analysis 2 included Salford Predictive Modeler (https://www.salford-systems.com/), IBM SPSS 20 (http://www-01.ibm.com/software/analytics/spss/products/statistics/) and Microsoft Excel 2010.

Data and Analyses

Data for these analyses were extracted from the DOC information system data warehouse.

Both analyses required the development and inclusion of a risk measure because a small percentage of the population accounted for a large percentage of the DRs. Inmates with PDRDRs in the top 15% accounted for 82% of the PDRDR. To control for this risk, an actuarial tool was developed that estimated the probability of having a PDRDR in the top 15% of PDRDRs.

Modeling Risk

Procedures for developing the SGB risk model included (a) variable identification,[1] (b) modeling with potential variables, (c) testing potential variables, and (d) developing the final model with variables that remained predictive in the testing sample.

Analysis 1

PDRDRs were calculated (see Dependent Variable below) for the year prior to intervention implementation and the first year post the intervention implementation date. First, a t-test on risk scores between E-A and E-B was performed to ensure that the differences were not influenced by risk. Second, percent differences of the pre-post differences were calculated to provide an estimate of the size and direction of the difference. Finally, Chi-square, goodness-of-fit analysis, was used to determine if the difference in pre and post rates were statistically significant for both E-A and E-B.

Inmates moving from cell to cell across the IMU system was a serious limitation of Analysis 1. To address this limitation, multiple regression analysis was used to control for both moving inmates and the risk of having high PDRDRs.

Analysis 2

Multiple linear regression estimated the association between PDRDRs and spending at least 30 days in IMU E-B during the post period while simultaneously controlling for variables associated with risk of having high PDRDRs during the inmate's stay in the IMU. Again, during the study period, IMU inmates in the treatment group only spent time in E-B and the IMU inmates in the non-treatment group did not spend any time in E-B. Finally, the probability of having high PDRDRs (see below, Dependent Variable: Risk Measure) for each individual in the study was entered into the regression model along with group membership (treatment or non-treatment, described above).

Sample

Participants: Modeling Risk

Participants for the development of the risk measure for the regression analysis included all inmates who were placed and spent at least 30 days in the IMU system at SRCI from July 1, 2009 through August 20, 2015 (N=1,486 unduplicated inmates randomly selected from 2,500 unique unit episodes).

[1] The variable selection method used for the risk equation employed stepwise logistic regression. All available predictor variables were entered at step one and only statistically significant variables that were linearly related to the outcome were selected for the SGB model to avoid over-fitting.

Participants: Analysis 1

Participants for Analysis 1 included all inmates who spent any time in IMU E at SRCI during the period from April 7, 2012 through April 7, 2013 prior to implementation of NIPP (hereafter referred to as the Pre period), and the period after NIPP was implemented (hereafter referred to as the post period) from April 8, through April 7, 2014 (N=252 [n=139 for E-A; n=113 for E-B],unduplicated inmates representing 566 unique episodes [time spent in a given cell during pre or post periods]).

Participants: Analysis 2

Participants for the regression analysis included all inmates who were placed and spent at least 30 days in the IMU system at SRCI from April 7, 2013 through April 7, 2014. In addition, inmates in the non-treatment group were only included if they spent no time in E-B during the period (n=269 unduplicated inmates); and inmates in the E-B treatment group were only included if they had not spent any time in any other IMU (n=107 unduplicated inmates). Further description of the IMU system is provided below in the independent variable section.

Variables

Dependent Variable: Analyses 1 and 2

Discipline referrals (DRs) are reports written by correctional officers when an inmate’s inappropriate behavior exceeds certain criteria. The criteria are designed to reflect behavioral expectations for all inmates and the DRs are used to track the extent to which inmates are behaving inappropriately. All DRs are reviewed by managing staff and documented in the DOC information system.

Person-day-rates of discipline referrals served as the dependent variable for both analyses. They were calculated by totaling the number of discipline referrals that were documented in a particular IMU during a pre or post period and dividing them by the sum total number of days each and every inmate was in a particular IMU during a given period. For example, there were 48 DRs documented on IMU D during the pre-period; those 48 DRs were divided by 16,497 person days on IMU D during the pre-period for a rate of .002979 DRs per-person-days. The rate was calculated for E-A and E-B and the percent differences in pre-post rates were used as the metric in Analysis I (pre-post differences). The rate was also calculated for each individual inmate and entered in the linear regression as the dependent variable in Analysis 2.

Dependent Variable: Measuring Risk

The dependent variable for the risk modeling procedure was the *Top 15% of PDRDR*. To calculate the Top 15% of PDRDR the percentile rank of the PDRDR for the risk modeling dataset (N=1,486) was computed. Those inmates whose PDRDR percentile ranking was about the 85th percentile were scored 1; those below the 86th percentile were scored 0.

Independent Variable: Analysis 1

The independent variable for Analysis 1 was the group: E-A or E-B. Each IMU has two sides that are nearly identical. The NIPP was only available on E-B (treatment group); E-A served as the comparison group. All services/privileges provided for inmates on E-B were also provided on E-A except the NIPP (e.g., Dialectical Behavior Therapy, showers, and indoor and open ceiling exercise rooms).

Independent Variables: Analysis 2

The groups were different for Analysis 2. For this analysis, the comparison group (hereafter referred to as "Not E-B") consisted only of inmates who spent at least 30 days in any IMU other than E-B and did not spend any time in E-B during the post period. The treatment group (here after referred to as E-B) consisted only of inmates who spent at least 30 days in E-B and did not spend any time on any other IMU. The group variable that was entered into the linear regression was coded 1 if the inmate was in the E-B group and 0 if the inmate was in the Not E-B group.

The risk measure also served as an independent variable in Analysis 2. As described below, the model also included 4 independent variables that were associated with high PDRDRs. SGB logistic modeling procedures produce a score that indicates the probability of having high PDRDRs for each inmate. Those probability scores were entered into the linear regression as independent variables.

Results: Modeling Risk

Four variables remained in the final SGB model (listed by order of importance): (a) Prior PDRDRs, (b) mental health acuity (scale 0 through 3), (c), Development Disability (0=no disability present and 1= disability present), and (d) at least one prior admission to the IMU (dichotomous code; note that this variable was negatively associated with the outcome).

Although the outputs for SGB do not provide parameter estimates, they do provide important statistics, including a measure of relative importance of each variable in the equation.[2] The most important variable is scored 100 and each variable after is scored proportionately. For this model, Prior DRs per day was the most important variable (score=100); Mental Health Acuity was the next most import variable (score=33); Development disabilities was next (score=17); and prior IMU was last (score=11). Recall that Prior IMU was negatively associated with the outcome, so inmates who had a prior stay at IMU were less likely to be in the top 15% PDRDR. Not surprising, prior DRs per days was by far the most important variable in the model.

The Area under the Receiver Operator Characteristic Curve (AUC) for the model was .77, indicating relatively strong predictive accuracy.

Results: Analysis 1

The difference between E-A and E-B on the risk scores (i.e., the predicted probabilities of being in the top 15% of PDRDRs) was not statistically significant ($t(250) = .493$, $p = .626$), indicating that the groups were equivalent in terms of risk and appropriate for comparison. Table 1 reports the number of person days, number of DRs, and the PDRDRs for E-A and E-B during the pre and post periods of Analysis 1. Clearly, the number and rate of DRs increased (up 16%) for E-A, and decreased for E-B (down 10%).

[2] In essence, variable importance is equivalent to a variable weight, or the relative amount that each variable contributes to the model.

Table 1. Pre and Post Number of Person Days, Number of DRs, and PDRDRs by IMU E side A and B.

Unit	Number of Episodes	Pre DRs	Post DRs	Pre Person Days	Post Person Days	Pre PDRDR	Post PDRDR	Percent Difference	Chi-Square	*p*
E-A	261	38	47	7450	7934	0.0051	0.0059	16.10%	-2.71	<.01
E-B	305	51	47	7879	8037	0.0065	0.0059	-9.70%	2.21	<.05

Discussion: Analysis 1

The data indicated that DRs went down on E-B after NIPP was implemented. Moreover, as RDRDRs deceased in E-B as hypothesized, RDRDRs increased on E-A. In practical terms, Table 1 implies that if both sides of the IMU were at full capacity for the pre and post-periods, E-A would have had 45 DRs in the pre period and 52 DRs in the post period (an increase of 7); E-B would have had 57 DRs in the pre-period and 51 DRs in the post-period (a decrease of 6), a substantial reduction (13 total) in real world conditions.

However, it is not clear whether the effects were due to NIPP or movement of inmates in and out of E-B, which is a common practice in the IMUs. Analysis 2 is an attempt to address this limitations.[3]

Results: Analysis 2

Table 2 reports the descriptive statistics of the two groups in terms of demographics, variables in the risk equation, predicted probability of being in the top 15% of PDRDR, and PDRDRs. Neither race nor age came into the predictive model, but they are reported here for reference. Interestingly, although the E-B group on average had higher predicted probabilities of being in the top 15% of PDRDRs, it was not because they had higher prior PDRDRs. The E-B inmates were higher risk because a large proportion of them had acute mental health problems/developmental disabilities.

Table 2. Table 2. Descriptive statistics of risk & demographic variables

Group	n	White	Mean Age	Mean Prior PDRDR	Mean Mental Health Acuity	Percent Developmental Disabled	Percent Prior IMU	Mean Predicted Probability of being in the top 15% of PDRDR	Mean PDRDR
E-B	107	64%	32	0.0112	1.18	20%	27%	0.188	0.0021
Not E-B	269	58%	29	0.0115	0.76	9%	17%	0.165	0.0027

[3] This certainly is not the only limitation to this study. See the Discussion for further examples.

Table 3 presents the results of the multiple linear regression modeling PDRDRs as the dependent variable with the risk measure and group participation as independent variables. Although the difference in group membership was not technically statistically significant (*p* =.057), it was extremely close. As hypothesized, the negative parameter estimate suggests that the PDRDR rate was lower for the inmates in E-B after controlling for risk. Adjusted $R^2$for the model was .21.

Table 3. Linear Regression Model Coefficients*

	Unstandardized Coefficients		*t*	Statistical Significance
	B	Std. Error		
(Constant)	-.002	.001	-3.722	.000
E-B	-.001	.001	-1.909	.057
Predicted Probability of Top 15% PDRDRs	.031	.003	10.144	.000

*Dependent Variable: PDRDR

Discussion

As a whole, the results from both analysis suggest that NIPP might have reduced problem behavior. However, without a more rigorous research design it is difficult to be sure if those reductions were a result of NIPP implementation. Unequivocal conclusions would require a design that included random assignment and controlled access to NIPP with replication of the methods and findings. Because of the design inadequacies, numerous limitations blur the findings and temper the results. Examples include (a) staff intention to provide intervention, (b) videos that did not include nature imagery, or (c) random variation. In addition, we do not know if some videos were more powerful than others, nor what dosage is optimal. At this stage, there is no assurance that the reduction in PDRDR found in both analysis were due to the NIPP. Further research needs to address these and other limitations before definitive conclusions can be drawn. That said, the results do suggest that although it is not quite “evidence- based,” NIPP is certainly a “promising practice,” and should be implemented and investigated further.

References

Friedman, J.H. (1999). Stochastic gradient boosting. Technical report, Stanford University.

Acknowledgements

Staff at SRCI and DOC

Without the cooperation and collaboration of staff at SRCI this research would not have been possible. OYA Research would like to thank the following staff (listed alphabetically) who helped on this project and provided services to the inmates in the most difficult circumstances:

Brad Cordes, Officer; Brenda Brooks, Officer; Charles Anderson, Lt.; Colette Peters, Director, DOC; Cyndi Waggoner, Behavior Health Services Qualified Mental Health Professional; David Jantz, Lt.; Jeff Duncan, Research Analyst; Kevin Karpati, Officer; Mark Dayton, Officer; Mark Nooth, Superintendent, SRCI DOC; Michael Lea, Officer; Michael Payne, Officer; Nathen Johnson, Sgt.; Paul Bellatty, Research Manager, DOC; Randy Gilbertson, Captain; Renee Smith, Behavior Health Services Manager; Robert Keltz, Officer; Sandy Glassey, Lt.; Shane Palmer, Sgt.; and Tom Jost, Captain

Researchers from University of Utah, Northwest Ecotherapy, and California Academy of Sciences

This research was also a result of a collaborative effort on the part of numerous researchers. OYA Research would like to thank the following professionals whose contribution cannot be calculated:

Nalini Nadkarni, Ph.D., Professor, University of Utah; Emily Gains Crockett, MS, University of Utah; Patricia Hasbach, Ph.D., Northwest Ecotherapy, Eugene, Oregon 97401 USA; and Tierney Thys, Ph.D., California Academy of Sciences, San Francisco, California 94118 USA

We would also like to thank the following researchers for helpful comments and edit on this document:

Paul Bellatty, Ph.D., Research Manager, OYA; Phil Getty, Ph.D., Senior Researcher, OYA; Nalini Nadkarni, Ph.D., Professor, University of Utah; and Kristi Racer, Ph.D., Senior Researcher OYA

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