Evidence From the Past: AI Decision Aids to Improve Housing Systems for Homeless Youth

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Abstract

Could an AI decision aid improve housing systems that assist homeless youth? There are nearly 2 million homeless youth in the United States each year. Coordinated entry systems are being used to provide homeless youth with housing assistance across the nation. Despite these efforts, the number of homeless youth still living on the street remains very high. Motivated by this fact, we initiate a first study to create AI decision aids for improving the current housing systems for homeless youth. First, we determine whether the current rubric for prioritizing youth for housing assistance can be used to predict youth's homelessness status after receiving housing assistance. We then consider building better AI decision aids and predictive models using other components of the rubric. We believe there is much potential for effective human-machine collaboration in the context of housing allocation. We plan to work with HUD and local communities to develop such systems in the future.

1 Introduction

There are nearly 2 million homeless youth in the United States each year. These are young people between the age of 13 and 24 who are homeless, unaccompanied by family, living outdoors, in places not fit for human habitation, and in emergency shelters (Toro, Lesperance, and Braciszewski 2011). The consequences of youth homelessness are many, including many preventable problems such as exposure to violence, trauma, substance use, and sexually transmitted disease (Toro, Lesperance, and Braciszewski 2011). A critical solution to improve long term outcomes for homeless youth is to quickly and efficiently help the homeless youth find stable housing situations. Indeed, there are many nonprofit organizations and public sector programs designed to do this. In almost all communities in the United States, the number of youth experiencing homelessness exceeds the capacity of the housing resources available to youth (Housing and Urban Development (HUD) 2015). This situation leaves communities with the terrible predicament of trying to decide who to prioritize for the precious few spots in housing programs which are available at any given time. Most communities have moved to what is referred to as a Coordinated Entry System. In such systems, most agencies within a community pool their housing resources in a centralized system. Persons who are seeking housing are first assessed for eligibility for housing, which usually includes HUD-defined chronic homelessness, other criteria such as veteran status, and vulnerability. Based on these assessments, persons are prioritized for housing and placed on waiting lists until appropriate housing becomes available in the community (Housing and Urban Development (HUD) 2015). Despite these efforts, most of the prioritization decisions are made by humans manually working in the housing communities using a simple rubric. Could an AI decision aid help humans make informed prioritization decisions? In this research report, we provide machine learning analyses and tools that could be of use to communities. We view this research report as a precursor for building a (physical) AI decision aid system/assistant that would help to improve the current housing systems in the future.

1.1 Our Goal

HUD is steadfast in wanting community housing systems to be systematic, evidence-based and grounded in research (Housing and Urban Development (HUD) 2015; 2016). Despite of this, save for a few exceptions (e.g. (Focus Strategies 2017)), the current housing allocation system for youth has not been evaluated for its success. As a result, the goal of this report is to see if we can evaluate the success of the current system using the data from the HUD's Homelessness Management Information System (HMIS), the primary repository for data on homeless services delivery in the U.S. If we can uncover (which we have) new insights in the current system and move toward new human-machine synergy, there is a potential to make a major impact in policy and societal outcomes. In particular, this report is an initial foray into seeing if AI decision aids and machine learning tools could enhance and improve upon the current vulnerability assessment tools: The Next Step Tool for Homeless Youth and the TAY Triage Tool (Rice 2017). Our study will provide a roadmap and guide into building better AI decision aid tools in the future.

1.2 Current Approach for Housing Prioritization

HUD offers many mandates, guidelines, and best practices recommendations to communities who want to house youth (Housing and Urban Development (HUD) 2015; 2016). In most Coordinated Entry Systems for homeless youth, housing agencies within a community pool their housing resources in a centralized system. First, a homeless youth enters a centralized intake location (e.g. emergency shelters, street outreach workers, or drop-in centers) to sign up for housing support. There, they are assessed for housing eligibility and vulnerability/risk. All this information is then entered into the HMIS. Then, based on these assessments, a case manager or a team of housing navigators decide how that youth is to be prioritized for housing. They youth is then placed on a waiting list until appropriate housing becomes available in the community.

Although communities may decide for themselves what risk/vulnerability assessment tool to use, the most frequently used tool for assessing the risk levels of youth is the Next Step Tool (NST) for Homeless Youth developed by OrgCode Consulting Inc. and Community Solutions and thus we focus our analyses on this tool.[1] Roughly speaking, the NST is a set of multiple-choice, dichotomous, and frequency-type questions to measure a youth's vulnerability based on his/her history of housing and homelessness, risks, socialization and daily functions, and wellness. Based on the results of NST, the youth will be assessed by a score from 0 to 17.

1.3 The Main Deficiency of the Current System

In many communities, based on the recommendations provided in the NST documentation, youth who score 8 to 17 are designated "high risk" youth and prioritized for Permanent Supportive Housing (PSH), a resource-intensive housing program which includes "wrap-around" social services for youth to assist them in remaining stably housed. Youth who score lower (the 4-7 range) are typically referred to Rapid Rehousing (RRH) which is a short-term rental subsidy program that infrequently has many social services attached. Some youth who score low (less that 4) may not ever receive housing resources. For many providers and communities, this step is often painful as the desire to help all homeless youth is foremost in the minds of every provider. The NST scoring recommendations are not a hard and fast set of rules, but as we show in our analyses, most communities follow these cut points when assigning housing to youth.

However, the NST is a general vulnerability measure, not tied to a particular outcome, and no research has been conducted to date which links this tool to particular outcomes, particularly long-term housing stability. As noted by many communities, the housing stability of a youth as they exit a program is often the most robust measure of success (Rice 2017). That is, they want to assign youth to the appropriate housing programs in order to maximize the youth's chances of being stably housed in the future. For instance, if a youth is placed in PSH, a successful outcome would be continuation of stay unless they transition to stable unsubsidized housing. For those receiving RRH, remaining a stable renter without further government assistance is a positive outcome. Such outcomes, however, might not have any positive correlation with the youth's risk levels.

These decisions are made by people working in the housing communities based on simply cut scores. Is this the only option? Could we provide AI decision aids that leverage other information in the system to make better prioritization decisions? We hope to answer these questions in this report.

1.4 Our Contribution

In this report, we provide insights and AI decision aid tools that would help the communities to understand and evaluate the current prioritization process outlined above. In particular, using the past housing assignment data of homeless youth, we:

a) Determine whether the NST score is an effective predictor for predicting youths' probabilities of successes;

b) Propose to build and learn an interpretable function that computes the probability of success of each youth to a homelessness exit[2] by leveraging various components of the NST.

Since our decision tools will be used by housing communities, it is important for the tools to be explainable and easy to use. As such, we focus on learning interpretable classifiers such as logistic regressions and decision trees.

The remainder of this paper is organized as follows. In Section 2, we discuss the dataset obtained from Ian De Jong (Orgcode), as part of a working group called "Youth Homelessness Data, Policy, Research" led by Megan Gibbard (A Way Home America) and Megan Blondin (MANY), which includes members of HUD, USICH, and ACF, as well as researchers from USC (Rice) and Chapin Hall at the University of Chicago (Morton). In Section 3, we show how we can use the NST scores to predict the youths' probabilities of successes. We then propose to learn explainable classifiers/functions to measure and compute these probabilities using other components of the NST in Section 4.

2 A Brief Description of the Data

The dataset consists of 10,922 homeless youth registered for housing services from the HMIS database from different communities in the U.S. These records were anonymized and provided by Iain De Jong of Orgcode. Some youth have already been assigned to some housing programs while others are still waiting for housing assignments. Each record has the youth's age, gender, LGBT status, ethnicity, type of community, and a list of responses to the NST questions (including NST score) assessing a youth's vulnerability.

Most importantly, for each homeless youth in the data, there are fields specifying his/her type of exit from homelessness and whether s/he is still living in the same type of

[1]The full name is Transition Age Youth - Vulnerability Index - Service Prioritization Decision Assistance Tool. The tool can be assessed at `http://orgcode.nationbuilder.com/tools_you_can_use`. This tool incorporated work from the TAY Triage Tool developed by Rice, which can be accessed at `http://www.csh.org/wp-content/uploads/2014/02/TAY_TriageTool_2014.pdf`.

[2]There are different ways homeless youth can exit homelessness; which include: being assigned to housing programs, going back to live with family members, and finding a stable living on their own.

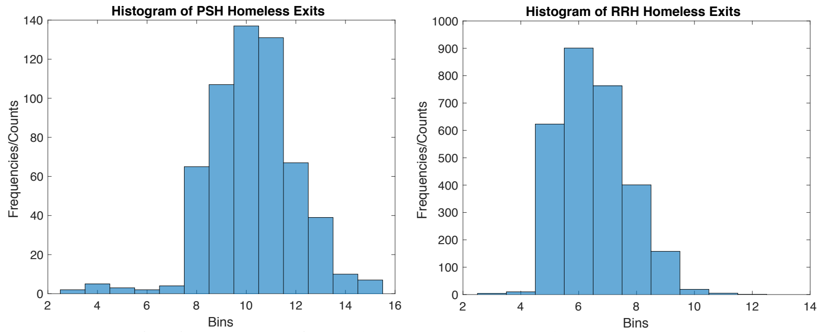

Figure 1: **Histograms of the Youths' NST Scores vs. PSH (left) and RRH (right) exits**. Left and Right: Bin range = [2.5 15.5] and bin width =1.

Table 1: **Basic Statistics of the Data.** #Y = Number of Youth, TofE = Type of Exits, #SH = Number of Youth Still Housed, and AvgNSTS = Average NST Scores

#Y	TofE	#SH	AvgNSTS
1145	Self Resolve	873	4.21
1259	Family	1006	4.65
1103	Unkown	N/A	6.38
2885	RRH	2209	6.52
3610	Pending	N/A	6.84
8	Boarding Home	8	6.875
54	SSVF	28	7.11
579	PSH	474	10.24
211	Incarcerated	N/A	10.25

exit after a fixed time period (a.k.a. Still Housed). The still-housed responses indicate whether a housing program was successful for the youth; "Yes" answers indicate a youth is still stably housed, a positive outcome; and "No" as indicates a youth has exited housing assistance and returned to homelessness, a negative outcome. Table 1 lists the number of youth in each type of exit in the data.

From the data, a large number of youth are still waiting for housing assignments and/or have been lost to the housing system. In many cases, some homeless youth went to live with their family members (Family) or were able to find to find housing themselves (Self Resolve). There are three main types of housing programs in the dataset: supportive services for veteran families (SSVF), permanent supportive housing (PSH), and rapid re-housing (RRH). Based on the data set, most communities have assigned high risk youth (with NST scores between 8-17) to PSH and moderate risk youth (with NST scores between 4-7) to RRH (Figure 1).

Given the data, our main goal in this paper is to understand how the features of a youth affect the probability that a youth will have positive outcomes (i.e. still-housed) given different types of exits from homelessness. In particular, we are interested in finding good predictors (i.e., features) that would help us to build robust models for predicting a given youth's different probabilities of success for different types of exits. Due to the small sample sizes of Boarding Home and SSVF, we are going to focus on Family, PSH, RRH, and Self Resolve exits in this paper.

3 Prioritization Tool: The NST Score

Since the NST score is the current suggested guideline for prioritizing youth into housing, we begin by studying the probability of a successful outcome as a function of the youth's NST score. In particular, we want to learn an interpretable function that would tell us a youth's probability of success (i.e., positive still-housed outcome) for a particular type of exit. Our plan is that, subsequently, communities can use our function as a decision aid to assist in determining the probability of success for a particular youth in a specific housing program. Such human-machine interaction will provide improved decision-making in the allocation of youth to housing programs. As discussed earlier, we are interested in youth that have Family, PSH, RRH, and Self Resolve types of exits from homelessness. In addition, we are interested in youth that either have or have not been assigned to any housing program. As such, we designate Non-Housing Program exits for youth that have Family or Self Resolve exits and Housing Program exits for those that have been assigned to either PSH or RRH.

3.1 Training Classifiers

Due to their explainability and ease of interpretation for end users, we focused on learning logistic regression and decision tree classifiers for each type of exit (Tibshirani 2011; Lipton 2016; Ribeiro, Singh, and Guestrin 2016). Moreover, we require the classifier to output class posterior probabilities for each of our classifiers.[3] To learn our classifiers, we use 80% and 20% of the data, pertaining to the type of exit, for training and testing, respectively. We use 10-fold cross validation in the training set to find the best hyperparameters to regularize the classifiers (L1-norm for logistic regression and depth for the decision tree). For constructing the decision (classification) trees, we consider the standard CART model to build a binary tree and select nodes/features and values to split based on Gini's diversity index (Breiman et al. 1984). For each split, we consider all the possible pairs of features and values. To control the depth of the tree, we

[3] Logistic regression classifier returns class posterior probabilities by default, decision tree classifier can return the percentage of the majority label at the leaves. This is known as calibration, or, more specifically, platt scaling, in the machine learning literature.

Table 2: **Learned Logistic Regressions and Decision Trees.** NH = Non-Housing Program Exit, H = Housing Program Exit, F = Family Exit, P = PSH Exit, R = RRH Exit, S = Self Resolve Exit.

Logistic Regressions	NH	H	F	P	R	S
AUROC	0.75	0.52	0.77	0.66	0.55	0.75
Constant	4.48	1.56	4.56	4.99	2.17	5.66
NST Score Weight	-0.68	-0.045	-0.63	-0.33	-0.15	-1.03

Decision Trees	NH	H	F	P	R	S
AUROC	0.71	0.52	0.73	0.62	0.54	0.71

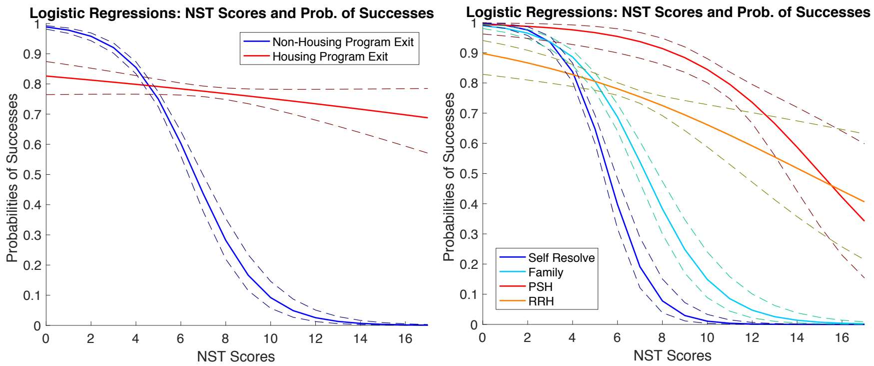

Figure 2: **Logistic Regressions of (Non-)Housing Program Exits (Left) and Individual Exits (Right).** Dotted lines = 95% Confidence Intervals for Prediction.

use cross validation to select the best minimum number of nodes at the leaves.

3.2 Performance Measure

We measure the predictive performance using the area under the receiver operating characteristic curve (AUROC). The ROC is constructed for the learned logistic regressions based on the true positive rate (true positive divided by true positive plus false negative) and the false positive rate (false positive divided by false positive plus true negative) points for each possible cutoff posterior probabilities in the test data. We then compute the area under the ROC. Roughly speaking, the AUROC is equal to the probability that a randomly chosen youth with a positive still-housed outcome ranks above (i.e, has a higher probability of success) than a randomly chosen youth with a negative still-housed outcome. Thus, higher AUROC indicates that the logistic regression is able to distinguish the classes effectively. AUROC is particularly useful in our setting because the unbalanced nature of our data ($\approx 76 - 82\%$ positive outcomes) as the standard 50% cutoffs for computing accuracy could provide us with a representative model rather than a discriminative model.

3.3 Results

In Table 2, we report the average AUROC over 100 different 80% and 20% splits of our data into training and testing. We omit reporting the small standard deviations for brevity. Once we have evaluated the predictive performance of our model, we report the parameters of the learned logistic regressions using all of the data as the training data. In all of the learned logistic regressions, the NST score weights are negative – indicating a negative correlation between the NST score and the probability of success (see Table 2). Using the NST score as the only feature, the logistic regression and decision tree classifiers for Non-Housing exit, Family exit,

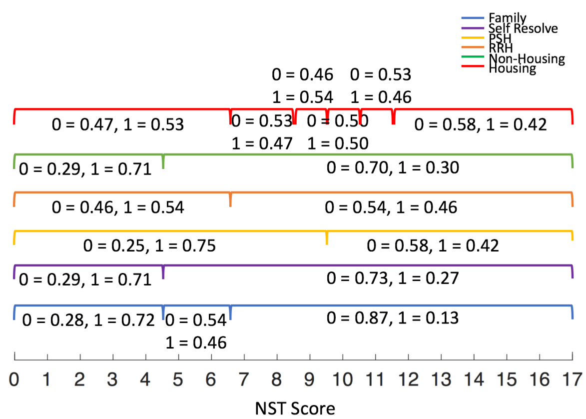

Figure 3: **Decision Boundaries of the Learned Decision Trees.** The probabilities of successes are displayed around the decision intervals (i.e., 1 = 0.53 denotes the probability of successes is 0.53).

and Self Resolve exit are reasonable predictive models. The performance of our classifiers, however, for overall Housing exits and RRH exits is only slightly better than a random guess. We will see if we can build better classifiers for different exits in the next section by adding more features.

From the left plot of Figure 2, we observe that (a) there is a negative correlation between the NST score and the probabilities of success for both Non-Housing Program and Housing Program exits, (b) the high scoring youth with no-housing support are more likely to return to homelessness than the low scoring youth, (c) youth with medium to high (≥ 5) NST scores tend to be more successful with housing support than without, and (d) the housing support seems to be most beneficial to high scoring youth (i.e., greatest increase in relative chance of success). From the right plot of Figure 2, we observe youth in PSH have a higher probability

Table 3: **AUROC of Logistic Regression and Decision Tree for Each Type of Exits.** NH = Non-Housing Program Exit, H = Housing Program Exit, F = Family Exit, P = PSH Exit, R = RRH Exit, S = Self-resolve Exit.

Type of Exits:	NH		H		F		P		R		S	
Classifiers:	LG	DT	LG	DT	LG	DT	LG	DT	LG	DT	LG	DT
Baseline	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
DOM	0.61	0.69	0.59	0.58	0.58	0.61	0.50	0.52	0.60	0.59	0.65	0.74
COM	0.50	0.53	0.50	0.49	0.49	0.52	0.50	0.47	0.50	0.49	0.51	0.55
NSTS	0.75	0.71	0.52	0.52	0.77	0.73	0.66	0.62	0.55	0.54	0.75	0.71
NSTQ	0.69	0.62	0.70	0.68	0.72	0.62	0.60	0.57	0.71	0.69	0.68	0.62
NSTT	0.79	0.73	0.62	0.60	0.77	0.69	0.63	0.59	0.65	0.63	0.86	0.78
NSTQ+NSTS	0.76	0.72	0.70	0.69	0.77	0.73	0.65	0.64	0.73	0.71	0.79	0.74
NSTT+NSTS	0.80	0.78	0.62	0.60	0.77	0.75	0.66	0.61	0.65	0.63	0.86	0.85
NSTA	0.79	0.79	0.70	0.69	0.77	0.75	0.65	0.63	0.73	0.71	0.86	0.85
NSTA+COM	0.79	0.79	0.70	0.69	0.76	0.75	0.65	0.63	0.73	0.71	0.86	0.85
NSTA+DOM+COM	0.79	0.79	0.70	0.69	0.76	0.75	0.65	0.63	0.74	0.72	0.86	0.86

of success than youth in RRH when NST scores are less than 15. Youth who score less than 4 have a higher probability of successfully exiting homelessness to Family or Self Resolve relative to RRH placements.

Figure 3 shows the decision boundaries of the learned decision trees for Non-Housing Program, Housing Program, Family, PSH, RRH, and Self Resolve exits. The line represents the range of the NST score. For each exit, we plot its decision intervals. In general, from the decision boundaries, youth with low NST scores have more than a 50% probability of being successful while youth with high NST scores have lower probabilities of being successful. Using only the NST score, the decision boundaries of Non-Housing Program, Family, and Self Resolve exits seem to be able to differentiate youth. The decision boundaries of Housing Program and RRH do not seem to be discriminative (i.e, give only $\sim$50% of probabilities of successes).

Table 4: **Subsets of Features.**

Subset	Description
DOM	Basic Demographic Information: Age, Gender, Race, LGBT Status
COM	Type of Communities: 16 Urban, Suburban, and Rural Communities
	Responses to the NST Questionnaires:
NSTQ	40 Questions (1 multiple choice, 9 numerical)
NSTT	17 Binary features tallying sub-responses
NSTS	1 NST Score
NSTA	NSTQ + NSTT + NSTS

4 Prioritization Tool: NST

As mentioned earlier, communities want to successfully place youth into housing programs which lead to the most positive outcomes. Our decision aid can assist them in making informed decisions, which can augment the chances of youth successfully exiting homelessness. In Section 3, we used only the NST score as a feature to build our predictive tools. In this section, our goal is to identify additional useful features that can help us to build better classifiers that can predict the youths' probabilities of success for different types of exits.

4.1 Features from the Youth and NST

We divide our features into the following subsets as in Table 4. The DOM features are basic demographic characteristics of the youth. The COM features are the type of community in which a youth lives. The NST evaluates the vulnerability of a youth based on his/her responses to the forty questions (NSTQ) about youth's history of housing and homelessness, risks, socialization, daily functioning, and wellness components. Each component scores a youth based on the responses to the questions within the component (NSTT). The NST score (NSTS) is the sum of the scores from the components. Using different combinations of the features, we consider learning logistic regression and decision tree classifiers and measure the performance using AUROC.

4.2 Logistic Regressions and Decision Trees

Table 3 shows the average AUROC of the classifiers for different subsets of features for each type of exit. First, the performance of the logistic regressions and decision trees is similar for most feature combinations. The COM features are not very useful and the learned models have AUROC only slightly better than random. The NST score (NSTS) alone is a reasonable predictor of the outcome. We tried different combinations of NSTQ, NSTT, and NSTS and found that we are able to build a better model with a higher/similar AUROC for all types of exits by combining all three subsets (i.e., NSTA). We also added COM and DOM to NSTA to see if we could improve the model. Unfortunately, the AUROC did not improve much. As such, we decided to use NSTA alone as the feature set to train our logistic regression and decision tree classifiers. For all of the exit types except Housing Program exit and PSH exit, our learned models are reasonable (with good AUROC scores). For the Non-Housing Program (H) exit, RRH (R) exit, and Self Resolve (S) exit, the AUROC increased by 15% to 30% over the AUROC of the learned logistic regressions using only the NST score. This provides some important indication that other parts of NST are useful for building better predictive models. On the other hand, our models for PSH seem to be much weaker than the other models for different types of exits, and the performance does not improve with more features. This is perhaps due to the noisy nature of the data.

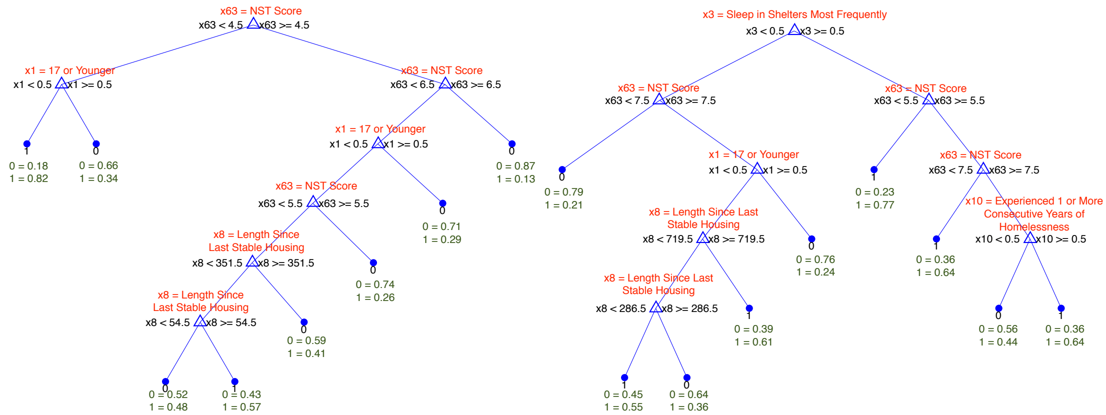

Figure 4: **Decision Trees for Non-Housing (left) and Housing (Right) Program Exits**. The probabilities of successes are displayed at the leave nodes (i.e., 1 = 0.82 denotes the probability of successes is 0.82). The deterministic decision is at 50% cutoff.

5 Significant Features of the Learned Models

Now that we have discussed the performance of the classifiers, let us look at important features in the model for each type of exit. For this purpose, we trained the classifiers using all of the available data for each exit. We highlight the important coefficients of the learned logistic regressions and decision trees. We can interpret the exponentiated coefficient of a predictor as the odds ratio when holding other predictors constant (i.e, a one-unit increase in the predictor value corresponds to some percentage of (multiplicity) increase in the odds of being successful).

5.1 Learned Models for Non-Housing and Housing Program Exits

At a high level, it would be useful for the communities to see whether the youth would benefit from receiving any type of housing. As such, we trained classifiers for Non-Housing program and Housing program exits in Section 4. In this subsection, we study the important features of the learned logistic regression and decision tree classifiers for these exits.

Table 5: **Non-Housing Program Exit: Top-6 (Ordered) Important Features of the Learned Logistic Regression.**

Weight	Description
-1.23	17 or younger
-0.74	Physical, Mental, Substance Abuse Issues
-0.55	Sleep Outdoors Most Frequently
-0.51	NST (Risk) Score
-0.39	Mental Health Issues
$+0.23$	Sleep in Trans. Housing Most Frequently

Learned Logistic Regressions Tables 5 and 6 show the top-6 important features for predicting the probabilities of successes. In both cases, youth that are 17 or younger have a lower chance of being successful. Quite surprisingly, youth that in transitional housing at the time of assessment have an increased chance of being successful without any additional housing support and these same youth are less likely to be successful when placed into a PSH/RRH housing program. For youth in Non-Housing Program exits (i.e. family/self resolution), those that have physical, mental, and substance abuse issues and those who sleep outdoors most frequently have a reduced chance of success. For the youth in Housing Program exits, those that sleep in shelters most frequently, have received some form of money, and have learning/developmental disability have increased chances of success.

Table 6: **Housing Program Exit: Top-6 (Ordered) Important Features of the Learned Logistic Regression.**

Weight	Description
-1.55	Sleep on Couch Most Frequently
-1.31	Sleep in Trans. Housing Most Frequently
$+0.60$	Sleep in Shelters Most Frequently
-0.23	17 or Younger
$+0.16$	Received Some Form of Money
$+0.14$	Learning/Developmental Disability

Learned Decision Trees Figure 4 shows the learned decision trees for the Non-Housing Program exit (left) and Housing Program exit (right). In both cases, NST score and 17 or younger are important decision nodes/features in the decision trees. In the Non-Housing Program exit decision tree, initial decision nodes are based on the NST score and 17 or younger features. As we go further down the tree, a youth's length of time since last stable housing determines his/her probability of success. The initial decision of the Housing Program exit decision tree is based on whether the youth sleeps in shelters most frequently. The subsequence paths are then based on the NST score, 17 or younger, and length of time since last stable housing features.

5.2 Learned Models for Family, PSH, RRH and Self Resolve Exits

In this subsection, we study the important features of the learned classifiers for each individual exit.

Learned Logistic Regressions Tables 7, 8, 9, and 10 show the top-6 most important features (in terms of weight) of the learned logistic regressions for different types of exits. In many of these classifiers, the locations where youth most frequently sleep and the NST scores are important features.

For Family exits (Table 7), we observe that a youth has a lower probability of success if the youth has been pregnant or has impregnated someone or has gender identity or sexual orientation issues. Surprisingly, youth that have an abusive relationship at home or elsewhere have an increased chance of having a successful exit to Family. For PSH exit (Table 8), traumatized youth have decreased probabilities of successes. Youth that have an abusive relationship at home or elsewhere have decreased chances of successes.

Table 7: **Family Exit: Top-6 (Ordered) Important Features of the Learned Logistic Regression.**

Weight	Description
-0.52	NST (Risk) Score
-0.51	Pregnant(ed) or Impregnated
-0.47	Sleep Outdoors Most Frequently
$+0.38$	Abusive Relationship at Home or Elsewhere
-0.35	Sleep on Couch or Outdoors Most Frequently
-0.35	Gender Identity or Sexual Orientation

Table 8: **PSH Exit: Top-5 (Ordered) Important Features of the Learned Logistic Regression.** Other features have a zero weight.

Weight	Description
-0.22	Abused or Traumatized
-0.15	NST (Risk) Score
-0.12	Sleep on Couch or Outdoors Most Frequently
-0.08	Sleep Outdoors Most Frequently
-0.02	Abusive Relationship at Home or Elsewhere

Table 9: **RRH Exit: Top-6 (Ordered) Important Features of the Learned Logistic Regression.**

Weight	Description
-1.59	Sleep on Couch Most Frequently
-1.53	Sleep in Trans. Housing Most Frequently
$+0.82$	Physical, Mental, Substance Abuse Issues
$+0.49$	Sleep in Shelters Most Frequently
-0.28	17 or Younger
-0.16	NST (Risk) Score

For RRH exit (Table 9), having physical, mental, and substance abuse issues and sleeping in shelters most frequently are positive factors for being successful in RRH. Youth with age of 17 or younger have lowered chances for success.

Finally, for Self Resolve exit (Table 10), youth that are 17 or younger or have some physical, mental, substance abuse, and medication issues have decreased chances of being able to successfully exit homelessness on their own. On the other hand, if a youth has used marijuana at 12 or younger, then the youth has an increased probability of being successful.

Learned Decision Trees Figure 5 shows our learned decision trees for the Family and RRH exits. For the Family exit, the tree starts with NST score in the root and the second level. The consequence paths are based on youth's responses to the length since last stable housing, abusive relationship at home or elsewhere, ran away from home, and the total emergency services. For RRH, sleep in shelters most frequency is the root of the tree. Then NST scores are use in the second and third level. The decision nodes are based on responses to length since last stable housing, risk of harm, and physical, mental, and substance abuse issues.

Table 10: **Self Resolve Exit: Top-6 (Ordered) Important Features of the Learned Logistic Regression.**

Weight	Description
-2.43	17 or Younger
-0.92	NST (Risk) Score
$+0.38$	Have used Marijuana at 12 or younger
-0.37	Physical, Mental, Substance Abuse Issues
-0.35	Medications
-0.34	Left Program due to Physical Health

6 Conclusion and Future Work

There is much potential for creating AI decision aids to improve housing systems. There is room for effective human-machine collaboration in the context of housing allocation. Our analyses show that NST scores have a small negative correlation when youth are given housing interventions but a profound negative trajectory as NST score increases without intervention. This suggests that assigning youth based on NST score is an effective intervention for assisting high risk youth. As such, the current housing assignment systems are providing a much needed housing resource to youth who would otherwise not achieve stable living on their own.

Assignment decisions based on NST scores, however, can be greatly augmented by additional predictive analytics and AI decision aids. As shown in Section 4, we can potentially improve the current housing systems by providing better interpretable and explainable tools/classifiers to estimate a youth's probability of success for each possible type of exit (i.e. PSH, RRH, Family, Self Resolve). Given these probabilities, social workers in each community can decide more precisely which housing intervention (PSH or RRH) is best or whether a given youth is likely to successfully achieve stability without help from the system (family housing, or self-resolution). Such information could do much to aid housing providers in making more informed decisions as to where to place a particular youth such that he/she is most likely to succeed. Moreover, providers may feel less anxiety about providing limited resources to some youth if they have information that suggests that a youth has a high probability of self-resolution or return to family. Thus, social service efforts can be focused more comfortably on those youth who are highly unlikely to succeed unless given more intensive resources such as PSH or RRH.

Moreover, our decision aids can further complement a human user. The ordered important features identified by the logistic regressions can serve as "red flags" for providers. For example, youth who have been abused or traumatized are less likely to be successful in PSH. This does not mean that providers should not place youth with such histories

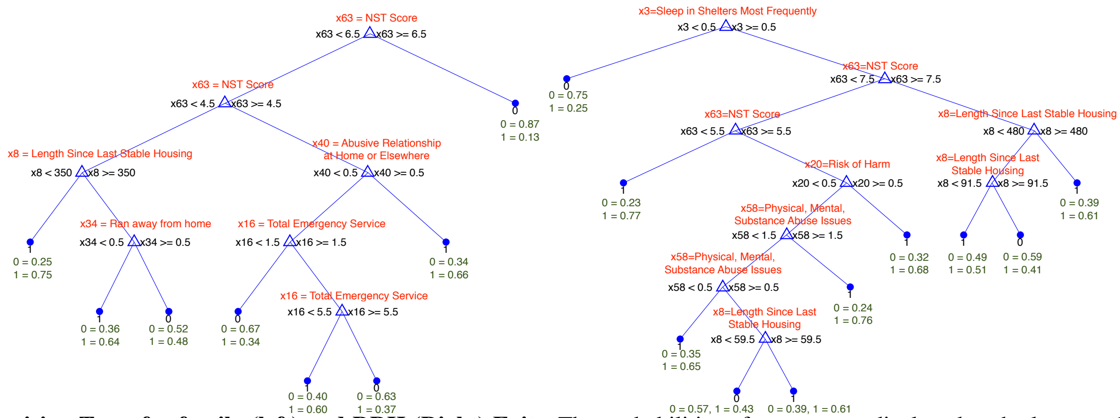

Figure 5: **Decision Trees for family (left) and RRH (Right) Exits**. The probabilities of success are displayed at the leave nodes (i.e., 1 = 0.75 denotes the probability of success is 0.75). The deterministic decision is at 50% cutoff.

into PSH. Rather, additional supports, perhaps mental health treatment for trauma, are needed for youth with such a history. Likewise, youth who are 17 or younger are much less likely to be able to succeed in RRH, suggesting that youth under 17 if given rental subsidies may need added attention beyond just the basic rental subsidy in order to improve their chances of remaining stably housed. Based on these preliminary findings, youth housing systems are an ideal setting in which to further explore the potential for AI decision aid systems for social service providers. These two basic additions which we have outlined here, do much to enhance the vulnerability screening currently in place and could greatly aid humans in making difficult decisions about which youth to place in which housing programs, and which youth within those programs may need additional attention in order to thrive. In the future, by continuing to work with HUD and local communities we hope to build an AI decision aid system that will provide humans with enhanced predictive criteria for outcomes of housing placements for particular youth. Finally, we plan to provide useful interactive assistants, such as graphical user interfaces, to facilitate and encourage the collaboration between machine (i.e., our system) and human users in the community.

Lesson Learned From Our Domain Many housing providers are resistant to using tools whether based on an index or AI/machine learning that will decide on housing placements in an automated fashion. Housing is a critical resource that profoundly impacts the well-being of youth. Thus, people working in the communities that provide housing assistance to youth feel that humans must remain a part of the decision-making process (Toro, Lesperance, and Braciszewski 2011; Rice 2017). Many current systems are often perceived as too rigid, and future systems must make room for human-machine interaction in decision-making.

Application of Our Methodology to Other Cognitive Assistance Projects Since machine learning is the basis of our work, similar techniques and tools can be used as AI decision aids for other cognitive assistance projects related to data analytics. While the application of machine learning tools is common in the AI community, machine learning analytic tools are novel and helpful in social work settings – providing domain experts with additional insights for solving their problems.

Acknowledgments

This research was supported by MURI Grant W911NF-11-1-0332.

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