# Getting to the root of the problem: A decision-tree analysis for suicide risk among young people experiencing homelessness

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Abstract

***Objective***: The assessment and prediction of suicide risk among young people experiencing homelessness (YEH) has proven difficult. Although a large number of suicide risk factors have been identified, there is limited guidance about their relative importance and the combinations of factors (i.e., profiles) that heighten risk. ***Method***: Using survey and social network methods, we gathered information about 940 YEH and their relationships. We then used a machine learning approach to construct Classification and Regression Tree models to predict suicidal ideation and suicide attempts. ***Results***: Thirteen variables were important correlates in the decision tree models. This included prominent individual risk factors (e.g., trauma, depression), *but* over half of them were social network factors (e.g., hard drug use). For suicidal ideation, the model had an area under the receiver operating characteristic curve (AUC) value of 0.79, with Accuracy of 68%, Sensitivity of 48%, and Specificity of 73%. For suicide attempt, the model had an AUC value of 0.86, with Accuracy of 71%, Sensitivity of 68%, and Specificity of 72%. ***Conclusions***: Effective suicide prevention programming should target the syndemic that threatens YEH (i.e., co-occurrence of trauma-depression-substance use-violence), including social norms in their environments. With refinement, our decision trees may be useful aids for suicide risk screening and guiding targeted intervention.

*Keywords*: homeless; suicide; machine learning; decision tree

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Suicide is a leading cause of preventable death among youth and young adults (Cha et al., 2018), but the issue is decidedly worse for those who are homeless (Fulginiti, Rice, Hsu, Rhoades, & Winetrobe, 2016). Most studies have found that one out of every three to four young people experiencing homelessness (YEH) report having suicidal thoughts in the past year (Kirst, Frederick, & Erickson, 2011; Lynn Rew, 2001). Even more troubling is that 20% of high school-aged YEH have attempted suicide in that same timeframe, which is double the rate among housed peers (Institute for Children, Poverty & Homelessness, 2018). These suicidal experiences are not only markers of intense suffering, but can also herald subsequent death by suicide (Runeson, Haglund, Lichtenstein, & Tidemalm, 2016). With nearly 3.5 million young people in the United States experiencing homelessness in 2017 alone (Morton et al., 2018), it is clear that a substantial number of them are vulnerable to suicidal crises.

At present, homelessness suicide research has predominantly focused on individual or personal attributes and relied on general linear modeling (GLM) procedures (i.e., regression, ANOVA). That work has helped to identify common suicidogenic correlates. Individual or personal attributes of YEH linked to greater suicidality include female gender (Yoder, 1999), Caucasian race (Unger, Kipke, Simon, Montgomery, & Johnson, 1997), marginalized sexual orientation identity (Noell & Ochs, 2001; Yoder, Whitbeck, & Hoyt, 2008), depression (Fulginiti et al., 2016; Yoder et al., 2008), substance use (Kidd & Carroll, 2007; Yoder et al., 2008), and history of trauma and posttraumatic stress (Barr, Fulginiti, Rhoades, & Rice, 2017; Yoder et al., 2008). Unfortunately, our extensive repository of suicide literature has not meaningfully improved our ability to predict suicidal behavior (Franklin et al., 2016). These prediction challenges are arguably more pronounced in the case of YEH given that most suicide research involves young people who are housed as compared to homeless. Substantive shifts and methodological innovations in YEH suicide research offer promise for better suicide risk prediction and prevention.

From a substantive standpoint, the individual- or person-centric story told in much scholarly and community discourse about suicide is incomplete (Fulginiti et al., 2016). More specifically, the premise of this story—suicides mostly happen due to intrapersonal risk—can minimize awareness regarding the power of social influence on suicide-related phenomena. Social connectedness, which is comprised of subjective (e.g., one's subjective sense of interpersonal relatedness) and structural (e.g., position, exposure to prosocial or risky behavior, and supportive resources in one's social network) dimensions of affiliation, serves as a prominent social influence that can affect suicide risk (Whitlock, Wyman, & Moore, 2014). For example, young people who perceive a stronger sense of connection with family tend to have fewer suicidal experiences (Whitlock et al., 2014), whereas young people who are socially isolated (Calati et al., 2019) or situated in social networks with depressed or suicidal friends tend to have more suicidal experiences (Fulginiti et al., 2016; Yoder, 1999; Yoder et al., 2008). Yet, we have limited insight into how the social networks (including network members' behavior and beliefs) of YEH impact their suicide risk. This is a disquieting omission given that young people who are embedded in social networks with more risky behavior are more likely to engage in high-risk activities (Barman-Adhikari, Rice, Winetrobe, & Petering, 2015; Rice, Milburn, &

Rotheram-Borus, 2007). Inclusion of person *and* environmental factors in YEH suicide research is imperative to inform a comprehensive suicide prevention approach in this population.

From a methodological standpoint, machine learning (ML) approaches represent innovative ways to leverage multidimensional datasets to improve prediction (Dwyer, Falkai, & Koutsouleris, 2018). Decision-tree (DT) methods represent well-known ML algorithms that are increasingly applied in suicide research. DT methods comprise a variety of analytic strategies (e.g., Classification & Regression Trees; CART) that involve classifying and segmenting a population into distinct subgroups whose members share characteristics that can promote or inhibit a given behavior (Lemon, Roy, Clark, Friedmann, & Rakowski, 2003). This makes DT methods especially well equipped to build clinical risk profiles (Bae, Lee, & Lee, 2015) and identify risky pockets within populations, which can inform targeted resource allocation (Lemon et al., 2003). DT methods are also more flexible than traditional GLM methods, like regression, in their ability to model multiple interaction effects and produce more interpretable results (Lemon et al., 2003). This is a significant advantage because moderation analyses can help us understand complex suicidal behaviors and design effective prevention programming for different groups (Musci et al., 2018). To date, most studies using decision-tree models have yielded area under the receiver operating characteristic curve (AUC) values that demonstrate moderate accuracy in delineating those who are and are not experiencing suicidal ideation and behavior (median/mean AUC = .76/.78; Burke et al., 2018; Gradus, King, Galatzer-Levy, & Street, 2017; Hettige et al., 2017; Mann et al., 2008; Morales et al., 2017). However, no known DT models have accounted for social forces that emerge from social networks, which could improve model specification and risk prediction.

Suicide remains a conspicuously neglected problem in the social work profession despite persistent suicide disparities among disenfranchised populations that underscore the need for a social justice perspective (Fulginiti & Frey, 2018; Joe & Niedermeier, 2008; Maple, Pearce, Sanford, & Cerel, 2017). This includes a paucity of social work scholarship about suicide among YEH whose profound social disadvantage is rooted in social inequity. Making matters worse, we are not aware of any studies in leading social work journals that have focused on suicide using DT methods. Building social workers' familiarity with DT methods is important for at least two major reasons. Social workers almost invariably interact with high-risk and suicidal clients (e.g., Feldman & Freedenthal, 2006), and DT methods can be useful in guiding practice decisions. Moreover, DT methods may be favored on social justice grounds because the results from those analyses can speak for marginalized subpopulations, whereas regression results lend voice to the "average" population member (e.g., Forthofer & Bryant, 2000).

To date, no known study has adopted an ML approach to understand suicide risk among YEH and studies using ML approaches in other populations have not accounted for social network features that may improve risk prediction. The current study sought to leverage an ML approach in the form of a DT analysis to identify the most important individual and social network features in predicting suicidal ideation and attempts among YEH. In doing so, the study also sought to identify distinct clinical profiles (i.e., combinations of features) that signal high vulnerability or resiliency with respect to suicidal ideation and attempts.

## Method

### Participants

The present study used data from a sample of 940 YEH (aged 13 to 29) who participated in a broader parent project designed to understand HIV/AIDS risk-taking behavior among young people experiencing homelessness (e.g., *blinded for review*). YEH were recruited between October 2011 and February 2013 from two drop-in centers that serve young people experiencing homelessness in Hollywood and Santa Monica, CA. The participating agencies delivered core services typical of drop-in centers, including the provision of case management, subsistence needs (e.g., food, shower), educational services (e.g., GED preparation), recreational opportunities (e.g., television/computer access), and job preparation (e.g., interview/resume support). Participants were, on average, 21 years of age (*SD* = 2.11). The vast majority of participants identified as being male (73%), heterosexual (76%), and people of color (61%). With respect to people of color, the breakdown was as follows: African American (24%), Latinx (14%), American Indian or Alaskan Native (3%), Asian or Pacific Islander (1%), and multiracial identity (19%). A minority of participants were enrolled in school (13%) or employed (13%). Participants, on average, first experienced homelessness at the age of 16 (*SD* = 3.99), had been homeless for a median of 30 months in their lifetime, and frequently used services at the drop-in center (i.e., somewhere between "a couple of times per week" and "every day or almost every day").

**Procedure**

All YEH receiving services during the data collection period were asked to participate in the study. Recruiters were positioned near the sole main entrance at the collaborating agencies to ensure that everyone who signed in for services during operating hours were approached for the study. Before beginning the study, the young people completed the agency's intake process to confirm that they met the eligibility requirements for the agency (and hence the study). The participation rate was 84% for the study.

Prior to data collection, informed consent was obtained from individuals aged 18 or older and informed assent was obtained from individuals 13 to 17 years old. The institutional review board (IRB) waived parental consent because youth under the age of 18 experiencing homelessness are unaccompanied minors without a parent or adult guardian. Data collection proceeded in two parts: a computerized self-administered survey and a social network interview. The computerized self-administered survey included an audio-assisted version for those with low literacy that could be completed in English or Spanish. Trained research team members conducted the social network interviews. Interviewers first explained to participants that they were collecting information about everyone in their social network during the previous month. Participants were asked to name every person they interacted with face-to-face, on the phone, or in written forms of communication, including text messages, emails, or through a social networking site. After each participant listed their network members, the interviewer went through a series of questions regarding the different attributes of each network member. The social network data was collected using an iPad app developed by the research team to reduce participant burden and increase participant engagement in the interview process. Participants received $20 in cash or gift cards as compensation for their time. The IRB at the principal investigator's home university approved the parent project.

**Measures**

*Dependent Variables.* Suicidal ideation was assessed with a question that asked, "During the <u>past 12 months</u>, did you ever seriously consider attempting suicide?" Suicide attempt was assessed with a question that asked, "During the past 12 months, how many times did you actually attempt suicide?" Responses were dichotomized to indicate the presence or absence of suicidal ideation and suicide attempt. These items were adopted from the Youth Risk Behavior Survey (Centers for Disease Control and Prevention [CDC], 2011).

*Independent Variables.* Independent variables were organized into two sets of variables: (a) personal or individual characteristics and (b) social network characteristics. The *personal or individual characteristics* included information about sociodemographic attributes (e.g., race/ethnicity, gender, sexual orientation, education) as well as mental health (e.g., depression, trauma; Steinberg, Brymer, Decker, & Pynoos, 2004; Radloff, 1991), substance use (e.g., alcohol, marijuana, hard drug use; CDC, 2011), sexual risk behaviors (e.g., # sex partners; CDC, 2011), violence perpetration and victimization (e.g., weapon-carrying, IPV victim; CDC, 2011), justice system involvement (e.g., spending time in jail; Harris et al., 2009), online activity (e.g., time spent online; Rice, 2010), and homelessness indices (e.g., time spent homeless; age first homeless; Young & Rice, 2011).

The *social network characteristics* included information about network members' attributes, including relationship types (i.e., family, friends, intimate partners, home-based peers, street-based peers); frequency of contact; substance use behavior (e.g., hard drug use); sexual risk behavior (e.g., unprotected sex); social support provision (e.g., emotional or tangible support), and encouragement/rejection of risky behavior. Network features were examined with respect to the number of network members with an attribute and the proportion of network members with an attribute (e.g., Rice, 2007). All of the measures for these social network variables have been employed in other published research (e.g. Barman-Adhikari et al., 2016; Barman-Adhikari et al., 2015; Fulginiti et al., 2016; Rice, 2010).

Overall, 117 independent variables—chosen predominantly based on empirical and theoretical support or relevance (e.g., Barr et al., 2017; Fulginiti et al., 2016; Kidd & Carroll, 2007; Noell & Ochs, 2001; Unger et al., 1997; Yoder, 1999; Yoder et al., 2008)—were evaluated for their classification utility in the generation of decision trees as described in the analysis section. However, only 13 variables were found by the algorithms to meaningfully contribute to the construction of the decision trees (i.e., feature importance > 0); measures for variables that contributed to the decision tree construction are detailed below. As in other work with large sets of candidate independent variables (e.g., Dykxhoorn et al., 2017; Morales et al., 2017), space considerations precluded the description of measures for candidate variables that did *not* contribute to the tree construction.

*Decision Tree Construction: Personal or Individual Variables*

*Age*. Age (in years) was assessed with a single self-explanatory, self-report question.

*Age First Homeless*. Age first homeless was assessed with a single self-report question that asked, "How old were you the first time you became homeless or did not have a regular place to stay?" (Young & Rice, 2011).

*Trauma History.* Childhood trauma was assessed using eight questions about exposure to different types of traumatic events (UCLA PTSD Index for DSM IV; Steinberg, Brymer, Decker, & Pynoos, 2004). Events included (a) having been hit, punched, or kicked very hard at home; (b) having seen a family member hit, punched, or kicked very hard at home; (c) having been beaten up, shot, or threatened to be hurt badly; (d) having seen someone being beaten up, shot at, or killed; (e) seeing a dead body; (f) having an adult or someone much older touch your private sexual parts when you did not want them to; (g) having heard about the violent death or serious injury of a loved one; (h) having been physically forced to have sex when you did not want to. Dichotomous responses were summed to reflect the number of traumatic events that YEH had experienced. The internal consistency (Cronbach's alpha) for the measure was .82 in the current study.

*Depressive Symptoms*. Depressive symptoms were assessed with the 10-item Center for Epidemiologic Studies Depression Scale (CES-D; Radloff, 1991). Each item is rated on a 4-point Likert scale, with response options ranging from 0 ("rarely or none of the time") to 3 ("all of the time"). A sum score was created, with higher scores indicating a greater number of depressive symptoms. The internal consistency (Cronbach's alpha) for the measure was .80 in the current study.

*Hard Drug Use.* Hard drug use was assessed with three questions that asked about frequency of lifetime use of cocaine/crack, methamphetamine, and heroin [i.e., "During your life, how many times have you used (hard drug)]?". Responses to the three questions were summed to created a hard drug use variable, with higher scores indicating higher frequency of lifetime drug use episodes. This measure was derived from items adopted from the Youth Risk Behavior Survey (CDC, 2011). The internal consistency (Cronbach's alpha) for the measure was .75 in the current study.

*Fighting Behavior.* Fighting behavior was assessed with a single question that asked, "During the past 12 months, how many times were you in a physical fight?". Response options included (a) 0 times, (b) 1 time, (c) 2 or 3 times, (d) 4 or 5 times, (e) 6 or 7 times, (f) 8 or 9 times, (g) 10 or 11 times, or (h) 12 or more times. This item was adopted from the Youth Risk Behavior Survey (CDC, 2011).

*Decision Tree Construction: Network Variables*

*Network Hard Drug Use*. Network hard drug use was assessed with a derived variable that was created to indicate the proportion of people in one's network who used hard drugs (i.e., # of people who use hard drugs/total # of network members). The proportion can range from 0 (i.e., no one in the network uses hard drugs) to 1 (i.e., everyone in the network uses hard drugs).

*Network Tangible Support*. Network tangible support was assessed with a derived variable that was created by summing the number of people in one's network who were a source of tangible support. A network member was classified as a source of tangible support if one could borrow money from the person (e.g., Frost, Meyer, & Schwartz, 2016).

*Home-based Friend Network Presence*. Home-based peer presence was assessed with a derived variable that was created to indicate the proportion of people in one's network who were friends before becoming homeless (i.e., # of people who are home-based friends/total # of network members). The proportion can range from 0 (i.e., no one in the network is a home-based friend) to 1 (i.e., everyone in the network is a home-based friend).

*Home-based Friend Tangible Support*. Tangible support from home-based friends (i.e., friends met before becoming homeless) was assessed with a derived variable that was created to indicate the proportion of people in one's network who were home-based friends that provided tangible support (i.e., # of home-based friends who are sources of tangible support/total # of network members). The proportion can range from 0 (i.e., no one in the network was a home-based friend that provided support) to 1 (i.e., everyone in the network was a home-based friend that provided support).

*Street-based Friend Emotional Support*. Emotional support from street-based friends (i.e., friends met after becoming homeless) was assessed with a derived variable that was created to indicate the proportion of people in one's network who were street-based friends that provided emotional support (i.e., # of street-based friends who are sources of tangible support/total # of network members). The proportion can range from 0 (i.e., no one in the network was a street-based friend that provided support) to 1 (i.e., everyone in the network was a street-based friend that provided support).

*Network Objection to Risky Behavior*. Network objection to risky behavior was assessed with a derived variable that was created to indicate the proportion of people in one's network who would object to substance use and sexual risk-taking behavior (i.e., # of people who object to any of these risky behaviors/total # of network members). The proportion can range from 0 (i.e., no one in the network objects to risky behavior) to 1 (i.e., everyone in the network objects to risky behavior).

*Network Size*. A variable was created to indicate the number of people nominated in someone's social network.

## Data Analysis

### *Main Analysis*

A Classification and Regression Tree (CART) model was used to predict suicidal ideation and suicide attempts among YEH. CART model analysis, a subset of decision tree analysis, can handle both continuous and dichotomous variables and analyze interactions between a large number of explanatory variables (Lemon et al., 2003). Tree-based models explore available data by recursively partitioning it into sub-groups, identifying the best combination of predictions for a given dependent variable. At each such partitioning step, the “best” independent variable with the “best” cutoff value is selected, and two separate groups are created with maximum homogeneity within each group and maximum heterogeneity between them (Baneshi et al., 2017). This binary splitting process is then repeated until stopping criteria are reached. Thus, this analysis creates a tree structure, which allows for easy interpretation and clinical application of the results, a well-known advantage of this modeling approach (Lemon et al., 2003).

To choose the “best” independent variable and cutoff value at each partitioning step, we used the Gini impurity measure (Baneshi et al., 2017; Breiman, 2017). The optimal dividing variable will lead to a Gini impurity index of zero (all cases in the sub-node belong to a single target category), while dividing variables that do not advance learning will lead to a Gini impurity index of 0.5 (cases in sub-node equally belong to all target categories). For CART, the Gini impurity measure is calculated for each possible dividing variable using (in our case) the two options available for the dependent variable. Then, the variable leading to the division with the lowest Gini impurity measure is chosen, and the process is repeated for the subpopulation created by partitioning the data according to this variable. To avoid overfitting the model to the training data, stopping rules were applied (Sandri & Zuccolotto, 2008). Consistent with stopping criteria in prior work (Baneshi et al., 2017; Timofeev et al., 2004), the minimum number of observations for the interim and leaf nodes in the tree models was set to 30 and 10, respectively;

the tree depth limit was set to 5; and the Gini impurity improvement threshold was set to 0.005 (Handley et al., 2016; Hill et al., 2017).

For each of the two DT models (i.e., suicidal ideation and suicide attempt), we used a random process to divide the dataset into training data (75% of the analytic sample) and testing data (25% of the analytic sample). The training dataset was used to create the tree model and identify the most important independent variables (feature importance). Then, the model was used to predict the dependent variable of the testing dataset. Based on the prediction results, AUC, accuracy, sensitivity, and specificity metrics were computed (Hajian-Tilaki, 2013). The AUC metric indicates the overall classification performance of the model and denotes the area under the receiver operating characteristic curve (ROC) (Hajian-Tilaki, 2013). The ROC curve for a binary classifier is created by plotting its sensitivity vs 1-specificity graph at various classifier thresholds. A random guess is denoted by the diagonal line x = y, whereas an ROC curve that arcs high above the x = y line indicate a classifier with improved performance. Accordingly, the larger the area under the ROC curve is (AUC), up to a value of 1.0, the greater the predictive capabilities of the model. Notably, the AUC is a metric that balances both sensitivity and specificity, which results in a better representation of performance in comparison to accuracy when there is class imbalance. Listwise deletion was used to address missing data in the main analyses (Ginkel, Linting, Rippe, & Voort, 2019), which resulted in analytic sample sizes of 586 and 587 for the suicidal ideation and suicide attempt DTs, respectively. To create the tree models, we used the python scikit-learn package (Pedregosa et al., 2011), which implements the CART model and supports training and testing.

*Ancillary Analysis*

Three ancillary analyses were conducted to provide additional perspective about the DT performance. First, we sought to examine the contribution of the social network variables to DT performance. To do so, we repeated the main analyses *without* using social network independent variables. This permitted a comparison of DT performance using social network information (i.e., main analysis results) and not using network information (i.e., ancillary analysis results).

Second, we sought to examine DT performance using a more advanced technique for handling missing data. To do so, we re-ran the main analysis using multiple imputation by chained equations (MICE), which has emerged as a principal method for addressing missing data (Buuren & Groothuis-Oudshoorn, 2010). Multiple imputation addresses a serious shortcoming of the listwise deletion method used in our main analysis, namely a loss of statistical power (King & Zeng, 2001). Informed by prior work (Alasalmi, Koskimäki, Suutala, & Röning, 2015; Belanche, Kobayashi, & Aluja, 2014), we used the following process: (1) the dataset, including missing values, was divided into a training set (75% of the total sample) and testing set (25% of the total sample), (2) the training set data was imputed 50 times, merged into a single dataset, and used to train the decision tree, (3) the testing set data was concatenated with the stacked training data set, imputed 50 times, and extracted from the training set for prediction, and (4) each of the 50 complete test datasets were used for prediction. Thus, for each sample in the test dataset, 50 predictions were produced, and a majority vote was used to form the final prediction for each test sample. This permitted a comparison of DT performance using listwise deletion (i.e., main analysis results) and multiple imputation for missing data (i.e., ancillary analysis results).

Third, we sought to compare our DT performance to another traditional prediction model. To do so, we performed a multivariate logistic regression prediction model using variables that were deemed meaningful or important by the decision tree analysis.

## Results

### ***DT Performance: Main Analyses***

#### **Suicidal Ideation Decision Tree**

Ten variables contributed to the construction of the decision tree for predicting suicidal ideation (in order of importance): (1) sum of traumatic childhood experiences, (2) lifetime hard drug use, (3) depression score, (4) proportion of street friends providing emotional support, (5) proportion of network members engaging in hard drug use, (6) proportion of network members providing tangible support, (7) current age, (8) proportion of home-based friends providing emotional support, (9) proportion of network members objecting to risky behavior, and (10) network size. Therefore, the number of traumatic childhood experiences was the independent variable that best discriminated between YEH who did and did not report suicidal ideation, but all of the other variables added predictive value by further distinguishing these groups. Feature importance values for each predictor are shown in Table 1. The importance of each feature is computed as the (normalized) total reduction of the Gini impurity criterion brought by that feature.

<Insert Table 1 here>

The tree built by the CART algorithm is shown in Figure 1. It was comprised of 4 depth levels with 20 nodes. Each node represents a subgroup (hereafter referred to as a “group”) of participants identified through the partitioning of data according to the predictors/cutoff values used to construct the decision tree. As a result, each group is defined by a given characteristic or set of characteristics (i.e., profile). Particular attention should be paid to the "Sample" and "Risk" values in the figure; the "Sample" value indicates the proportion of participants (expressed as %) in a given group and the "Risk" value indicates the probability (expressed as %) that the participants in a given group experienced suicidal ideation. Due to the sizable number of groups, we herein focus on the three highest risk groups and three lowest risk groups. However, all group profiles delineated by the decision tree, along with their risk probability, can be found in Table 2. Notably, the groups are numbered to facilitate cross-referencing across text, figures, and tables.

<Insert Figure 1 here>

Group 13 was identified as the highest risk group, with an 87% chance of suicidal ideation; the profile included a high number of traumatic childhood experiences (>3.5), a high depression score (>14.5), and a low proportion of home-based friends providing emotional support (≤0.24). Group 9 was identified as the second highest risk group, with an 83% chance of suicidal ideation; the profile included a low number of traumatic childhood experiences (≤3.5), high number of lifetime hard drug use experiences (>5.5), and younger current age (≤19.5). Group 17 was tied for the third highest risk group (with Group 6), with a 78% chance of suicidal ideation; the profile included a high number of traumatic childhood experiences (>3.5), a low depression score (≤14.5), a high proportion of street-based friends providing emotional support (>0.68), and a low number of network members providing tangible support (≤2.5).

Groups 18 and 20 were the two lowest risk groups, with a 0% chance of suicidal ideation. The Group 18 profile included a high number of traumatic childhood experiences (>3.5), a low depression score (≤14.5), a high proportion of street-based friends providing emotional support

(>0.68), and a high number of network members providing tangible support (>2.5). The Group 20 profile included a high number of traumatic childhood experiences (>3.5), high depression scores (>14.5), high emotional support from home-based friends (>0.24), and a large social network (>9.5 network members). Group 8 was the third lowest risk group, with a 4% chance of suicidal ideation; the profile included a high number of traumatic childhood experiences (>3.5), low number of lifetime hard drug use experiences (≤5.5), and a high proportion of network members who object to risky behaviors (≤0.23).

This DT model had an AUC value of 0.79, with Accuracy of 68%, Sensitivity of 48%, and Specificity of 73%.

<Insert Table 2 here>

**Suicide Attempt Decision Tree**

Six variables contributed to the construction of the decision tree for predicting suicide attempts (in order of importance): (1) depression score, (2) proportion of network members objecting to risky behavior, (3) age first homeless, (4) proportion of home-based friends in one's network, (5) sum of traumatic childhood experiences, and (6) frequency of fighting. Therefore, depression severity was the independent variable that best discriminated between YEH who did and did not report a suicide attempt, but all of the other variables added predictive value by further distinguishing these groups. Feature importance values for each predictor are shown in Table 1.

The tree built by the CART algorithm is shown in Figure 2. It was comprised of 4 depth levels with 16 nodes. In Figure 2, the "Risk" value indicates the probability (expressed as %) that the participants in a given group experienced a suicide attempt. Group 12 was identified as the highest risk group, with an 87% chance of making a suicide attempt; the profile included a low number of traumatic childhood experiences (≤4.5) who not only experienced high depression but particularly severe depression (>20.5). Group 6 was identified as the second highest risk group, with an 82% chance of making a suicide attempt; the profile included a high depressive score (>16.5) and a high number of traumatic childhood experiences (>4.5). Group 8 was identified as the third highest risk group, with an 75% chance of making a suicide attempt; the profile included low depression score (≤16.5), younger age of first homelessness experience (>16.5), and more frequent instances of past-year fighting behavior (> 3.5).

Group 15 was identified as the lowest risk group, with a 0% chance of making a suicide attempt; the profile included a low depression scores (≤16.5), older age of first homelessness experience (>16.5), a high proportion of network members who object to risky behavior (>0.25), and a low number of traumatic experiences (≤4.5). Group 10 was identified as the second lowest risk group, with a 8% chance of making a suicide attempt; the profile included all of the same characteristics as Group 15, without the trauma attribute. Group 14 was identified as the third lowest risk group, with an 11% chance of making a suicide attempt; the profile included low depression score (≤16.5), younger age of first homelessness experience (>16.5), more frequent instances of past-year fighting behavior (> 3.5), and a large proportion of home-based friends in one's network (>0.23).

This DT model had an AUC value of 0.86, with Accuracy of 71%, Sensitivity of 68%, and Specificity of 72%.

<Insert Figure 2 here>

***DT Performance: Ancillary Analyses***

Table 3 compares results from the ancillary analyses and main analyses in the prediction of suicidal ideation and attempts. From a descriptive standpoint, the table shows that the DT in the main analysis performed equally well or slightly better than the ancillary logistic regression model on nearly all metrics. Additionally, the DT in the main analysis that used social network information performed marginally better than the ancillary model that did not use network information on all metrics. With the exception of the sensitivity value for suicide attempt, the ancillary DT model using multiple imputation yielded higher values on all metrics than the main DT model using listwise deletion. To further contextualize these descriptive results, we performed post-hoc analyses to examine whether or not differences in AUC values across models were statistically significant; according to Delong Test results (Delong, Delong, & Clarke-Pearson, 1988), the differences in AUC values across models did not reach statistical significance.

<Insert Table 3 here>

## Discussion

Although many studies have sought to identify factors that can aid in detecting YEH who are at risk for suicide, it is difficult to synthesize that information in ways that can efficiently guide clinical decision-making. This is the first known study to leverage ML in the form of a DT analysis to better understand and predict suicidal ideation and suicide attempts among YEH. Of note, the following discussion is concentrated on the findings from our main analyses unless specific reference is made to ancillary analyses.

The decision-tree (DT) analysis identified childhood trauma as the most important feature in discriminating YEH with and without suicidal ideation. This is consistent with research linking trauma to suicide-related outcomes (Krysinska & Lester, 2010; May & Klonsky, 2016). That the degree of trauma exposure elevates suicidal thinking is especially concerning for YEH because the vast majority of them endure traumatic events prior to homelessness and on the street (Barr et al., 2017; Bender, Thompson, Ferguson, Yoder, & Kern, 2014). Multi-level efforts, such as trauma-informed policy (Bowen & Murshid, 2015) and trauma-informed care in homelessness service settings (Hopper, Bassuk, & Olivet, 2010), are necessary to reduce trauma exposure and effects among YEH. Trauma-informed care raises awareness about trauma and generates opportunities for people to regain a sense of control and build coping skills (Hopper et al., 2010), which may protect against the development of suicidal ideation and behavior. Unfortunately, trauma interventions for YEH have only been sparingly evaluated (Davies & Allen, 2017). Many other individual characteristics—including drug use and depression—that emerged as predictors of suicidal ideation in the DT analysis have also been observed in prior work (Kidd & Carroll, 2007; Yoder et al., 2008). This reinforces the need for homelessness service providers to facilitate adequate mental health and substance use assessment and treatment (Bender et al., 2014; Slesnick, Guo, Brakenhoff, & Bantchevska, 2015; Tucker, D'Amico, Ewing, Miles, & Pedersen, 2017).

Additionally, the DT analysis identified depression as the most important feature in differentiating YEH who have and have not attempted suicide. This aligns well with the robust body of work showing that depression increases suicide risk (Ribeiro, Huang, Fox, & Franklin, 2018). In fact, our subgroup profiles revealed that high levels of depressive symptoms are often sufficient to make YEH highly susceptible to suicide attempt. As with suicidal ideation, personal characteristics, such as trauma and aggressive behavior, were also correlates of suicide attempt in our DT analysis. Trauma and aggressive behavior have been associated with suicide outcomes in previous studies (Liang, Flisher, & Chalton, 2003; May & Klonsky, 2016; Stack, 2014) and may actually facilitate the transition from suicidal thinking to behavior (May & Klonsky, 2016; Van Orden et al., 2010). Regrettably, YEH confront high levels of adversity over the life course that can produce syndemics (i.e., co-occurrence of aversive conditions, like depression, trauma, violence) and potentially increase risk of suicide attempt (Mustanski, Andrews, Herrick, Stall, & Schnarrs, 2013). Therefore, interventions that address structural factors (e.g., the social environment) to disrupt syndemic formation may be particularly beneficial (Mustanski et al., 2013). For example, we need to develop new strategies and implement proven strategies to curb violence victimization in the social contexts of YEH (e.g., Bender et al., 2018).

Even though the role of social network factors in the suicidal process remains ill-defined (Fulginiti et al., 2016), our work demonstrates that networks matter. Numerous social network characteristics were found to be prominent correlates of suicidal ideation and, to a lesser extent, suicidal behavior. In fact, over half of the factors identified as being important in our DT analyses were related to the network environments of YEH. This included attributes like emotional support from friends, tangible support, drug use, and objection to risky behavior in one's network. These results are not entirely unexpected given evidence that social support and deviant peer behavior are associated with suicide risk (e.g., Bell et al., 2018; Haynie, South, & Bose, 2006; Schutt, Meschede, & Rierdan, 1994; Winterrowd & Canetto, 2013). However, the current work advances the field by furthering our understanding of an expanded set of social network factors. In doing so, we showed that the norms operating in the environments of YEH deserve more attention in the context of suicide prevention programming. Therefore, the overarching message is that social network assessments and interventions may be a promising way to augment individual-level strategies (Fulginiti & Frey, 2018; Fulginiti et al., 2016). The good news is that using social network data to inform programming is becoming more feasible with greater access to social media data and open-source software that can facilitate timely, user-friendly network data collection and analysis (e.g., Perry, Pescosolido, & Borgatti, 2018). For example, the Network Canvas app supports interactive survey design, interviewing, and data management that can be customized based on program goals (https://www.networkcanvas.com). In addition, scholars have highlighted specific ways to use network information for suicide prevention programming. To illustrate, Fulginiti and Frey (2018) discuss the delineation of networks as part of safety planning while Pickering and colleagues (2018) discuss how network information can be used to strategically select peer leaders to diffuse the effects of gatekeeper training.

Moving beyond the relative importance of singular predictors, the decision-tree analyses also identified clinical profiles (i.e., subsets or configurations of characteristics) that discern YEH who are vulnerable to suicidal ideation and attempts. Although some high-risk profiles reflect combinations that would likely raise red flags for clinicians (e.g., high trauma + high depression + low social support = high SI risk), others are not so intuitive. Indeed, many of the profiles illustrate the potential hazards of overlooking social network markers that signal heightened risk or resilience. For example, YEH who exhibited low levels of depression and aggression (and earlier onset homelessness), but were embedded in networks with fewer home-based friends still had a 65% chance of suicide attempt (Group 13). In the same vein, YEH who exhibited low levels of depression (and later onset homelessness), but situated in networks of peers who did not object to risky behavior were at similarly elevated risk for a suicide attempt (Group 9). Furthermore, YEH with high personal drug use and lower trauma exposure were classified as being at low risk (22%; Group 15) versus high risk (72%; Group 16) for suicidal ideation based on their respective positioning in lower versus higher drug use networks. Moreover, YEH who had high levels of depression *and* trauma but also reported being in larger social networks with greater support from home-based friends had a *zero* percent probability of suicidal ideation (Group 20). These profiles highlight the potential limitations of routine mental health assessments or screeners (e.g., PHQ-9; Kroenke & Spitzer, 2002) that tend to place heavy emphasis on internalizing or other intrapersonal symptoms without accounting for environmental context.

Lastly, the performance of our decision tree in terms of prediction bears consideration. The area under the curve (AUC) value suggests that our model is 79% accurate in differentiating between YEH with and without suicidal ideation and 86% accurate in differentiating YEH who did and did not attempt suicide; these values, which can be interpreted as the average sensitivity value for all possible levels of specificity, correspond to a moderate level of accuracy (Streiner & Cairney, 2007). Our AUC values are also equal to or exceed those observed in most suicide studies using DT or similar classification analyses (Burke et al., 2018; Handley et al., 2014, 2016; Hettige et al., 2017; Mann et al., 2008; Morales et al., 2017). Even though our models exhibited other promising performance values as well (e.g., accuracy, specificity), we observed low sensitivity (e.g., Dykxhoorn, Hatcher, Roy-Gagnon, & Colman, 2017). Therefore, without refinement, the use of our model as a screener would limit the number of false positives but not false negatives. Although false positives are preferable to false negatives in suicide prevention, the ability to guard against false positives should not be devalued. False positives can lead to an inefficient use of resources (Handley et al., 2016; Hill, Oosterhoff, & Kaplow, 2017), which may need to be wisely allocated in under-resourced environments that frequently engage YEH (e.g., drop-in centers, shelters). Moreover, YEH are already stigmatized for experiencing homelessness (Kidd, 2007), so they may be particularly sensitive to and impacted by the threat of facing additional stigma when being erroneously flagged for follow-up about suicidal experiences. Yet, a screener with low sensitivity is highly problematic as a stand-alone system for detecting suicide risk; in this early stage of development, a reasonable approach may be to trial (and refine) our DT as a component of a broader surveillance and triaging system. To address low sensitivity, it may be beneficial to cost-weight the analysis as to minimize false negatives, but determining cost weightings can be complicated (Mann et al., 2008). With respect to our ancillary analyses, our DT approach compared favorably with logistic regression—a common benchmark—in predicting suicide outcomes; even though the AUC differences between models did not reach statistical significance, the DT approach holds several meaningful advantages over logistic regression (e.g., risk profile identification; interpretability) that have pragmatic implications for suicide prevention programming. Similar to other non-suicide research, we also found that using multiple imputation to address missing data can lead to better DT classification performance than more routine missing data techniques (e.g., listwise deletion; Twala, 2009).

From a pragmatic standpoint, suicide risk assessment can be an extraordinarily difficult endeavor. This is made more complicated in homeless service settings that are often not equipped with enough staff trained to address mental health issues (e.g., on-site counselors; Gardner, 2010). However, DTs may be deployed to maximize staff capacity by supporting them in making decisions about the efficient distribution of their limited resources. For example, being able to identify the largest high-risk groups can be useful when prioritizing program development decisions. In addition, groups of YEH who share a similar risk profile could possibly be targeted as a collective rather than as individuals. Assignment of YEH to risk tiers may also help to expedite treatment decisions (e.g., in-house treatment vs. external referrals). As a logistical matter, although DTs are attractive due to their interpretability (Lemon et al., 2003), a real-world DT implementation would ideally be supported by software to automatically output a person's risk profile (i.e., information in Table 2) as well as action steps based on risk levels that have been pre-defined by the unique homeless service setting.

*Limitations*

Our study offered a distinct perspective on YEH suicide, but it is not without limitations. Our study is retrospective, and thus our DT analysis cannot necessarily generalize to future suicide-related events as done in prospective work (Dykxhoorn et al., 2017). An important next step is to replicate our analytic approach using current and historical information about individuals to predict their prospective suicide outcomes (i.e., suicidal ideation and/or suicide attempts). Our YEH sample was recruited from drop-in centers in a limited number of cities, had relatively lengthy homelessness tenures (i.e., higher chronicity), and had an overrepresentation of males and heterosexual youth, which may not be representative of the larger YEH population (including YEH who face added stress due to their marginalized gender/sexual orientation identities). Relatedly, the distribution of suicide outcomes and risk factors (e.g. types of illicit substances) can differ based on geographic locale so our findings may not generalize to areas outside of our study region. Additionally, certain measures did not capture all facets of the intended constructs; for example, our measure of tangible support focused on money lending without assessing for other goods/services (e.g., food/shelter; Wenzel et al., 2012) and our measure of objection to risky behavior focused on substance use/sex risk but not other kinds of risky behavior linked to suicide outcomes (e.g., violence, delinquency; Ammerman, Steinberg, & McCloskey, 2018; Thullen, Taliaferro, & Muehlenkamp, 2016). As a data mining technique, decision tree analyses have also been critiqued for overfitting models that cannot be validated in other datasets, which manifests in DT variability across samples; although we took steps to avoid overfitting models (e.g., stopping rules), the reality is that there are different ways to address these concerns (e.g., random forests) and replication is needed to bolster confidence in our findings. Finally, although a broad range of individual and network predictors were used for model development, we could not capture all known suicidogenic (e.g., hopelessness; perceived burdensomeness) and protective (e.g., coping skills, self-esteem; Gauvin et al., 2019; Kim et al., 2019) factors.

## Conclusion

Suicide risk evaluation is a daunting endeavor that involves gathering and synthesizing information on a multitude of factors to inform clinical decisions. Discerning the importance of isolated risk factors as well as risky clinical profiles is critical to that endeavor. Our decision tree analyses produced new information, particularly detailed interaction effects via the branching of the tree structure, that provides a foundation for future work aimed at developing early warning assessment tools for clinicians and other service providers who work with YEH. The hope is that these tools can augment clinical assessments and help guide targeted intervention by alerting clinicians and other service providers to factors and profiles that can signal vulnerability in YEH.

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Table 1.

*Decision-tree results: Most important variables for predicting suicidal ideation and suicide attempt*

| Suicidal Ideation | | Suicide Attempt | |
|---|---|---|---|
| Variable | Importance Value | Variable | Importance Value |
| Trauma | 100 | Depression | 100 |
| Personal Hard Drug Use | 58 | Network Object Risky Behavior | 33 |
| Depression | 51 | Age First Homeless | 32 |
| Street Friend Emotional Support | 42 | Home-Based Friend Presence | 28 |
| Network Hard Drug Use | 34 | Trauma | 27 |
| Network Tangible Support | 32 | Fight | 19 |
| Current Age | 30 | | |
| Home Friend Emotional Support | 20 | | |
| Network Object Risky Behavior | 19 | | |
| Network Size | 19 | | |

*Note.* The importance of each feature is computed as the (normalized) total reduction of the Gini impurity criterion brought by that feature. Generally speaking, the feature importance score indicates how useful or valuable each feature is in the construction of the decision trees.

Table 2.

*Decision-tree-based subgroups: Profile characteristics as well as their probability of suicidal ideation (SI) and suicide attempt (SA)*

| **SUICIDAL IDEATION** | | | | | | **SUICIDE ATTE** | | | |
|---|---|---|---|---|---|---|---|---|---|
| # | % *P*(SI) | Characteristics | # | % *P*(SI) | Characteristics | # | % *P*(SA) | Characteristics *P*(SA) | # |
| 1 | 30 | Trauma (L) | 11 | 19 | Trauma (H)<br>Depression (L)<br>Street Friend Support (L) | 1 | 35 | Depression (L) | 9 |
| 2 | 64 | Trauma (H) | 12 | 65 | Trauma (H)<br>Depression (L)<br>Street Friend Support (H) | 2 | 71 | Depression (H) | 10 |
| 3 | 9 | Trauma (L)<br>Personal Hard Drug Use (L) | 13 | 87 | Trauma (H)<br>Depression (H)<br>Home Friend Support (L) | 3 | 51 | Depression (L)<br>Younger Age of First Homeless | 11 |
| 4 | 48 | Trauma (L)<br>Personal Hard Drug Use (H) | 14 | 58 | Trauma (H)<br>Depression (H)<br>Home Friend Support (H) | 4 | 19 | Depression (L)<br>Older Age of First Homeless | 12 |
| 5 | 44 | Trauma (H)<br>Depression (L) | 15 | 22 | Trauma (L)<br>Personal Hard Drug Use (H)<br>Older Current Age<br>Network Hard Drug Use (L) | 5 | 52 | Depression (H)<br>Trauma (L) | 13 |
| 6 | 78 | Trauma (H)<br>Depression (H) | 16 | 72 | Trauma (L)<br>Personal Hard Drug Use (H)<br>Older Current Age<br>Network Hard Drug Use (H) | 6 | 82 | Depression (H)<br>Trauma (H) | 14 |
| 7 | 54 | Trauma (L)<br>Personal Hard Drug Use (L)<br>Network Object Risky Bx (L) | 17 | 78 | Trauma (H)<br>Depression (L)<br>Street Friend Support (H)<br>Network Tangible Support (L) | 7 | 38 | Depression (L)<br>Younger Age of First Homeless<br>Fight (L) | 15 |
| 8 | 4 | Trauma (L)<br>Personal Hard Drug Use (L)<br>Network Object Risky Bx (H) | 18 | 0 | Trauma (H)<br>Depression (L)<br>Street Friend Support (H)<br>Network Tangible Support (H) | 8 | 75 | Depression (L)<br>Younger Age First Homeless<br>Fight (H) | 16 |
| 9 | 83 | Trauma (L)<br>Personal Hard Drug Use (H)<br>Younger Current Age | 19 | 67 | Trauma (H)<br>Depression (H)<br>Home Friend Support (H)<br>Small Network Size | | | | |
| 10 | 37 | Trauma (L)<br>Personal Hard Drug Use (H)<br>Older Current Age | 20 | 0 | Trauma (H)<br>Depression (H)<br>Home Friend Support (H)<br>Large Network Size | | | | |

*Note.* These subgroups (# column) were created via the branching of the decision trees. There were 20 subgroups in the suicidal ideation DT and 16 subgroups in the suicide attempt DT. The (H) stands for “high” and the (L) stands for “low”; these relative terms indicate whether the YEH in that group scored higher or lower than the DT-determined cutoff value for each specific variable. Specific cutoff values can be referenced in Figures 1 and 2. The (P) stands for probability; the values in that column refer to the probability (expressed as %) that YEH in a given subgroup experienced SI/SA.

Table 3.

*Comparison of Results for Main Analyses and Ancillary Analyses*

| | Suicidal Ideation (SI) | | | | Suicide Attempt (SA) | | | |
|---|---|---|---|---|---|---|---|---|
| | AUC | Accuracy | Sensitivity | Specificity | AUC | Accuracy | Sensitivity | Specificity |
| Main | .79 | 68 | 48 | 73 | .86 | 71 | 68 | 72 |
| Ancillary #1 (Without SN) | .75 | 67 | 46 | 71 | .82 | 70 | 58 | 71 |
| Ancillary #2 (With MI) | .84 | 71 | 54 | 75 | .88 | 77 | 49 | 83 |
| Ancillary #3 (With LR) | .77 | 67 | 45 | 73 | .84 | 71 | 57 | 74 |

*Note*. The AUC metric indicates the overall classification performance of the model. A higher AUC suggests that a model is better able to discriminate between suicidal and non-suicidal individuals. The difference in AUC values across models can be interpreted as the % difference in the models' ability to correctly classify individuals as suicidal (SI/SA) or not. Based on post-hoc analyses using the Delong Test (Delong, Delong, & Clarke-Pearson, 1988), the differences in AUC values across models did not reach statistical significance; the Delong Test results are not depicted in the manuscript for parsimony, but are available from the first author upon request. Importantly, the DT approach holds several meaningful advantages over logistic regression (e.g., risk profile identification; interpretability) that have practical implications for suicide prevention programming as described in the discussion section.

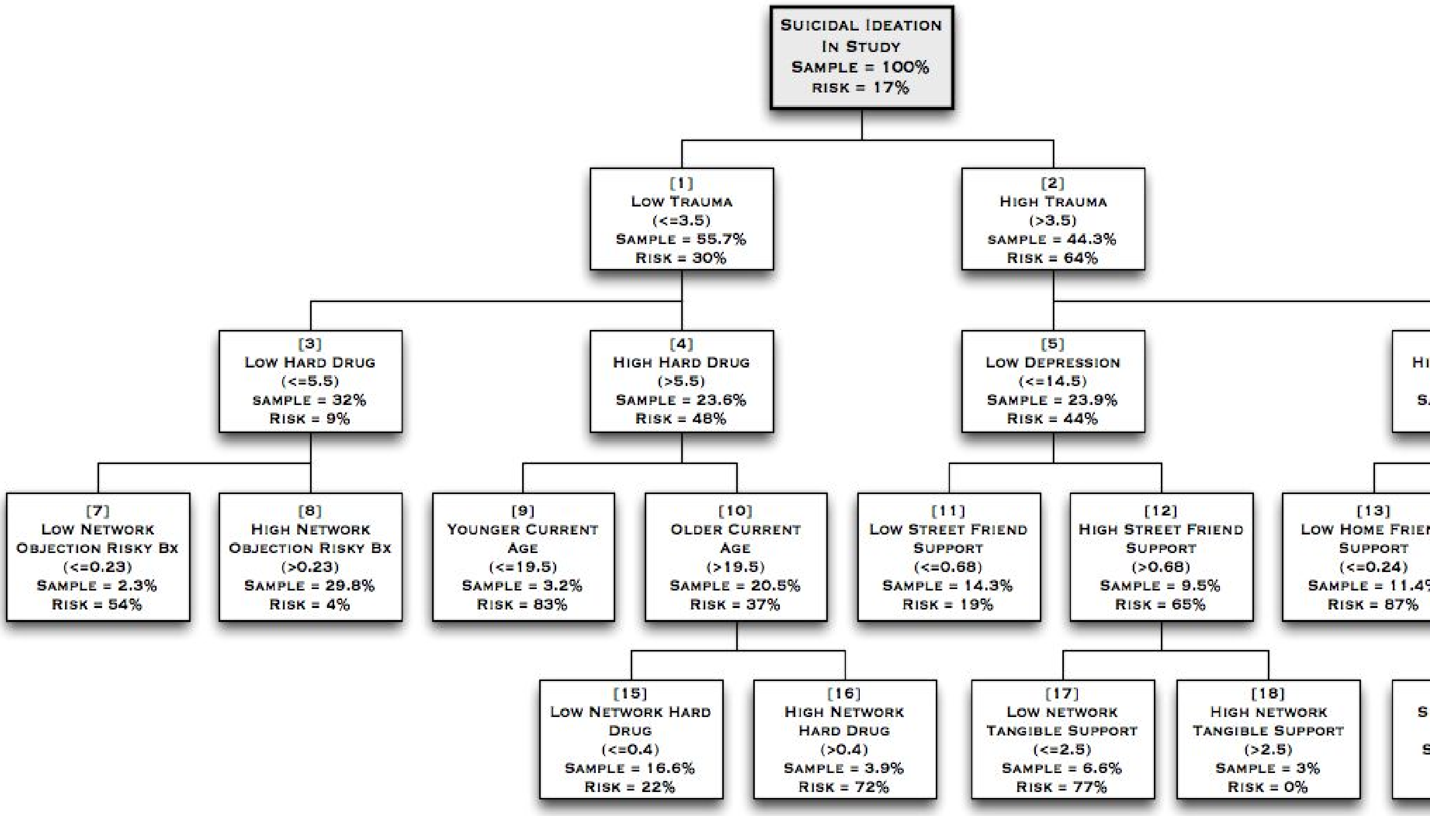


*Figure 1*. Decision Tree - Suicidal Ideation (SI): There are 20 tree nodes and 4 tree levels (not counting the node at the top, which indicates that 17% of ALL sample participants reported suicidal ideation). Each rectangle (i.e., tree node) represents a subgroup of the sample. Each subgroup is defined by the characteristic in the rectangle as well as the characteristic(s) in the connected rectangle(s) in the tree level(s) above it; this can be understood as the subgroup profile. The uppermost bracketed number in the rectangle is the subgroup #; this # can be cross-referenced in text and in Table 2. The number in parentheses below the defining characteristic is the specific cutpoint value on that variable that defines the subgroup. The “Sample” value indicates the % of our participants with that subgroup profile. The “Risk” value refers to the probability (expressed as %) that YEH in the subgroup experienced SI. For example, 29.8% of our participants had the profile for Group 8. The profile for YEH in Group 8 included: (a) fewer traumatic childhood experiences (b) fewer instances of personal lifetime hard drug use behavior and (c) social networks where a higher proportion of people object to risky behavior. YEH in Group 8 had a 4% chance of experiencing SI.

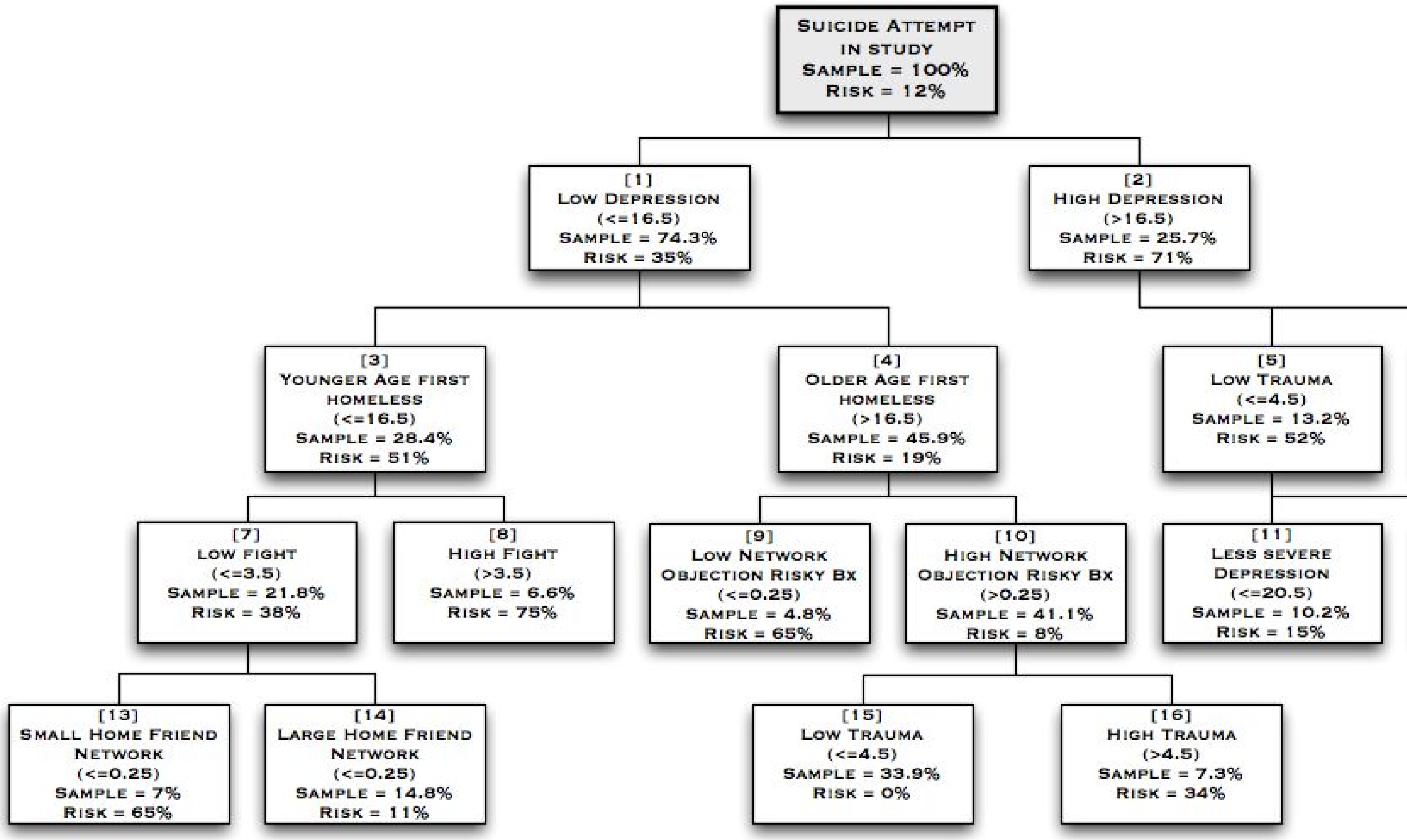


*Figure 2.* Decision Tree – Suicide Attempt (SA): There are 16 tree nodes and 4 tree levels (not counting the node at the top, which indicates that 12% of ALL sample participants reported a suicide attempt). Each rectangle (i.e., tree node) represents a subgroup of the sample. Each subgroup is defined by the characteristic in the rectangle as well as the characteristic(s) in the connected rectangle(s) in the tree level(s) above it; this can be understood as the subgroup profile. The uppermost bracketed number in the rectangle is the subgroup #; this # can be cross-referenced in text and in Table 2. The number in parentheses below the defining characteristic is the specific cutpoint value on that variable that defines the subgroup. The "Sample" value indicates the % of our participants with that subgroup profile. The "Risk" value refers to the probability (expressed as %) that YEH in the subgroup experienced SA. For example, 14.8% of our participants had the profile for Group 14. The profile for YEH in Group 14 included: (a) lower depression (b) first homeless at a younger age (c) fewer instances of fighting and (d) more home-based friends. YEH in Group 14 had an 11% chance of experiencing SA.