Identifying Dropout and Absenteeism Risk Using a Validated Measure in a Youth Mentorship Program

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**Abstract**

~~Adolescence serves as a crucial transitioning point into adulthood. It is important that these transitioning adolescents are provided quality mentorship as they make this important transition. Campus Connections, an evidence-based at-risk adolescent mentoring program, provides this support. However, Campus Connections, like many programs focused on improving adolescent outcomes, experiences adolescent dropout and lowered rates of attendance.~~~~This study utilizes a standardized risk measure to build a predictive model that measures the risk adolescent program dropout. Overall, internal, and external risk factors reported from adolescent caretakers are used as the main predictors of program dropout and attendance rate. Internal risk factors were the most predictive of program dropout and attendance rate throughout the course of the program. External risk factors appeared to be less predictive of the outcome variables across both models. Implications for intervention based on scores on the validated risk measure may help to reduce program dropout of adolescents in programs working with an at-risk adolescent population. Furthermore, reducing dropout and absenteeism allow adolescent populations to experience the full effects of mentorship support in order to produce better outcomes as they make the transition into adulthood.~~

*~~Keywords:~~* ~~dropout, absenteeism, mentorship, at-risk, adolescents~~

**Introduction**

The surgeons general report that 10%-20% of youth suffer from at least one psychological disorder; yet 75%-80% these youth do not receive appropriate evidence-based specialty services (Greca, Silverman, & Lochman, 2009). Making matters worse, qualified youth that participate may drop out of interventions designed to alleviate psychological symptoms. Although research is limited on the effects of dropping out from evidence-based programs, untreated children have higher risks for long term negative outcomes. (Abrahamse, Niec, Junger, Boer, & Lindauer, 2016). This presents a major barrier to the achievement of beneficial program effects. Evidence-based programs often have rigid curricula necessary to produce positive outcomes. Often times, evidence-based interventions must stay “on track” with their curriculum for ensured success (D. K. Wilson et al., 2009). Deviations from the fidelity of a particular curriculum, or failure to experience the whole program, reduces program efficacy (Erdem, Dubois, Larose, De Wit, & Lipman, 2016). As a result, money and resources are wasted providing services to adolescents who may not benefit from the program, and the affected child fails to receive the services that they need. In order to maximize resources and benefits to participants, efforts are needed to ensure that young people enrolled in intervention programs attend as much of the program as possible and complete the program. Despite this clear need, little research has been conducted to identify strategies to promote attendance and completion of intervention programs for youth in need.

To be sure, the identification of effective strategies to promote attendance and program completion will require comprehensive investigation. One natural starting place is to identify risk factors for poor attendance and dropout. Students at risk for school lowered attendance & dropout include individuals with disabilities (Sinclair, Christenson, Evelo, & Hurley, 1998), behavioral problems (Kennelly & Monrad, 2007), parental abuse/neglect, and teenage pregnancy (Curran Neild & Balfanz, 2006). Dropout risk factors may additionally be attributed to multiple characteristics within at-risk youth population such as family environment and negative social influences (Bronfenbrenner et al., 1986; Jozefowicz-Simbeni & Allen-Meares, 2002). School absenteeism is also associated with many negative factors such as violence, substance use, and teenage pregnancy (Kearney, 2008). Risk factors may stem from a wide variety of sources including, but not limited to poverty, gang-related activity and parental alcohol and drug abuse (Garringer, McQuillin, & McDaniel, 2017). The analogous research from school systems help to understand the detriments of poor attendance and dropout from a structured institution.

Establishing a similar typology of youth that are also likely to dropout or be absent from an at-risk youth centered intervention program may serve as a beneficial practice. Predictive models of youth program dropout have shown increasing levels in adolescent age is associated with higher odds of dropout (Baruch, Vrouva, & Fearon, 2009; Mendenhall, Fontanella, Hiance, & Frauenholtz, 2014). Additional evidence shows youth that have mothers with high internalizing symptoms in were predictive of program attrition in United States family populations (Abrahamse et al., 2016). O’Keeffe et al. (2018) also found that antisocial behaviors were predictive of dropout from adolescent therapeutic interventions. If risk factors could be successfully identified, and these risk factors could be measured prior to the start of the intervention, then program staff would have the opportunity to provide targeted attention to these vulnerable participants.

We can use these established risk factors to intervene early. Our goal with the current study is to determine if poor attendance and dropout in the context of 12-week mentoring program can be reliably predicted using a risk screening toolmeasure developed by Herrera, Dubois, & Grossman (2013) to identify youth in need of services. The 32-item assessment is completed by a parent or guardian and assesses the presence of 12 risk factors that describe personal or individual characteristics of the child (e.g., Academic challenges) and 20 risk factors that describe the child’s environment (e.g., Family stressors). Importantly, the assessment includes items pertaining to negative risk factors in a child’s life at multiple ecological levels (e.g., individual, family, school, neighborhood). Herrera and colleague’s assessment is free to use and already adopted by many intervention programs (Weiler, Boat, & Haddock, 2019). It is typically administered prior to program start. These are important features because if we find that this risk screening tool can reliably predict youth who will exhibit poor attendance or dropout of the program, then it may be an easily adopted technique that other programs can readily use to identify vulnerable participants and intervene before absenteeism or dropout commence. Therefore, we seek to understand how the risk screening tool will serve as a proxy to identify youth with a higher risk for dropping out and being absent from intervention programs.

**Methods**

*Participants & Procedure*

Our sample consists of youth who participated in the Campus Connections (CC) mentoring intervention. Campus Connections is a mentoring program for youth at heightened risk for poor developmental outcomes, such as behavior and emotional problems. It is flexibly designed to respond to the needs of a heterogeneous group of youth with varying risk levels. The program is grounded in theoretical and empirical research on positive youth development settings (Eccles & Appleton Gootman, 2002; Kelly, Ryan, Altman, & Stelzner, 2000; Tseng & Seidman, 2007) and Rhodes’ model of youth mentoring (Rhodes, 2005). See Haddock et al. (2013) and Weiler et al. (2015) for complete information on the program model.

Data were collected as part of a three-year grant funded by the William T. Grant (WTG) foundation. This WTG funded study incorporated a randomized control trial experimental study design. The goal of the three-year project was to compare the effectiveness of a “mentor family” youth mentoring model to the classic dyadic mentorship approach. More information of the youth mentor family approach may be read in Haddock et al. (2013).

Campus Connections typically occurs four nights a week (Monday – Thursday) during a regular academic semester. Twenty-eight youth are assigned to each night. Youth were randomly assigned to either the experimental mentor family condition or treatment-as-usual dyadic pairing mentorship condition. Study inclusion criteria include: Youth be aged 11-18 years of age, experience at-least one risk factor from the risk screening tool (Herrera et al., 2013), and available to participate during the CC operating hours. Participants could not have participated in previous CC sessions to be eligible for this study.

Participants were parents/guardian, and their youth. Youth were referred to the CC program through several community agencies including the local school district, juvenile justice system, Department Human Services, and various youth and family agencies. Upon receipt of the referral, trained CC staff contacted potential participants and conducted an intake appointment to determine program eligibility and obtain assent and parental consent. If eligible and willing to participate in the CC program, parent(s)/guardian(s) completed the risk screening tool (Herrera et al., 2013) prior to the start of the start of CC. Surveys were completed using Qualtrics, a web-based survey. The Institutional Review Board approved all the described procedures.

*Measures*

*Risk Screening Tool*

Herrera and colleagues’ (2013) 32-item risk screening tool was administered to each child’s parent of guardian at program intake (which occurred three months to one-week prior to the start of the program). Parents reported on the number of environmental risks (20 items) and individual risks (12 items) youth experienced by indicating either 1 (yes) or 0 (no). Environmental risk assessed economic adversity (e.g., family has difficulty paying bills), family stress (e.g., family member with drug or alcohol problems), and peer difficulties (e.g., no close friends). Individual risk assessed academic challenges (e.g., failing two or more classes), problem behavior (e.g., bullies others), and mental health concerns (e.g., exhibiting depressive symptoms). Items were summed to create a count of the total number of environmental risks and individual risks that youth experienced and a sum of the overall risk (a combination of environmental & individual risk); higher scores indicated that youth experienced and/or were exposed to a greater number of risks at baseline.

*Overall Statistical Procedures*

All descriptive statistics and analytic procedures were performed using R version 3.5.2 (R Core Team, 2018). A total of 24, twelve-week sessions, were analyzed. These sessions occurred over the course of three years, from Fall of 2015 to the Spring of 2018. For all statistical analyses, the 24 sessions were dummy coded to control for session differences. Furthermore, demographic variables such as youth age, sex, and ethnicity were controlled. Age was centered at the mean across all youth participants (*M =* 14.21, *SD* = 1.83).

*Analytic approach for modeling dropout*

Dropout from the program is defined as individuals that agreed to start the program, attended at least one session of CC, but proceeded to either lose contact with the program staff or formally drop out of the program. For instances in which a adolescent participant did not attend the CC program, efforts were made by program staff to contact the adolescent participant’s families. This was conducted by contacting the adolescent’s primary caregivers by phone, text message, and email. When there was no contact with the mentee’s family after two sequential weeks or more, the youth was considered a dropout.

Of the 675 mentees that started the CC program, a total of 61 (9.08%) dropped out and did not progress throughout the course of the entire program. To predict odds of dropout, three multiple logistic regression models were fit to assess predictors of dropping out of CC. Youth dropout out from the program (dropped = 1) was regressed on risk scores and all control variables. Model 1 assessed the entirety of the risk scale (All risk). Model 2 assessed the environmental risk subscale (Environmental risk). Model 3 assessed only the individual risk subscale (Individual risk). Adjusted odds ratios (OR) and 95% Confidence Intervals (CI) were computed for all three models.

Accurately predicting youth that dropped out of the program was also of interest. Risk measure thresholds and the ability to classify dropout are assessed by analyzing an adjusted Area Under the Curve (AUC) of the Receiver Operating Characteristics (ROC) curve. The adjusted AUC ROC curve analysis analyzes the model’s capabilities to correctly classify which youth will drop and stay in CC, after controlling for session and demographic variables.

*Analytic approach for modeling attendance*

Campus Connections program staff recorded attendance each week of the 12-week Campus Connections program. Instances in which the participant did not arrive to CC were marked as absent. If the participant arrived late, they were marked present.

Three Poisson regression models were used to assess the risk of absenteeism (max days absent = 11) with the predictor risk scores. An offset term was created to account for one session in Spring 2016 that experienced a snow day during the course of the program. This session was cancelled, and no make-up day was available for youth participants. For this specific session, the offset was set to ten for the session with a snow day because the max amount of days missed was ten. Of participants who did not drop from the program, the average days absent was 1.70 days (*SD* = 2.09).

Similar to the previously mentioned logistic regression models, Model 4 assessed the entirety of the risk scale, Model 5 assessed the environmental subscale, and Model 6 assessed the individual risk subscale. An adjusted incident rate ratio (*IRR*) of being absent from CC and corresponding 95% CIs were calculated.

**Results**

Descriptive statistics, separated by those who dropped and those who remained in the program across the 12 weeks, are shown in Table 1. Demographic variables (sex, ethnicity, and age) were self-reported by youth. Parent-reported risk scores are separated by total risk score (32 items), the environmental risk subscale (20 items) and the individual risk subscale (12 items) in Table 1.

Chi-square tests of independence were performed to assess group differences between dropout and both mentee sex and mentee ethnicity; no group differences were observed, χ2 (1, 656) = 1.26, *p* > .05 and χ2 (1, 656) < .01, *p* > .05, respectively.

Table 1

*Descriptive Statistics of Campus Connections Youth Participants*

|  |  |  |  |
| --- | --- | --- | --- |
|  | Dropped | | |
|  | No (n= 595) |  | Yes (n=61) |
|  | *n (column %)* |  | *n (column %)* |
| Mentee sex |  |  |  |
| Male | 352 (59.16%) |  | 31 (50.82%) |
| Female | 243 (40.84%) |  | 30 (49.18%) |
| Mentee ethnicity |  |  |  |
| White | 241 (40.50%) |  | 25 (40.98%) |
| Other | 354 (59.50%) |  | 36 (59.02%) |
|  |  |  |  |
|  | *M* (*SD)* |  | *M* (*SD)* |
| Mentee age | 14.15 (1.83) |  | 14.84 (1.65) |
| Parent-reported  risk measure scores |  |  |  |
| All Risk | 6.87 (3.82) |  | 9.00 (4.36) |
| Environmental Risk | 4.04 (2.82) |  | 4.90 (3.14) |
| Individual Risk | 2.84 (2.11) |  | 4.10 (2.44) |

*Dropout Results*

The overall risk scale, environmental risk subscale, and individual risk subscale were associated with higher odds of dropping from the CC program. Results from each logistic regression model are found in *Table 2*. The individual risk subscale was associated with the highest odds of dropping out as compared to youth who had continued enrollment in the program (*OR* = 1.22, 95% CI [1.08, 1.37]), followed by the overall the risk scale (*OR* = 1.12, 95% CI [1.05, 1.19]), and lastly the environmental risk subscale (*OR* = 1.11, 95% CI [1.01, 1.22]) after controlling for demographic variables and session attended.

An AUC ROC curve was fit for all subscales to detect their discriminability to detect dropout. The adjusted AUC showed poor discrimination for the overall risk, environmental risk and individual risk scale (adjusted AUC = .62, .60, and .58, respectively).

*Absenteeism Results*

The overall risk scale, environmental risk subscale, and the individual risk subscale were all associated with attendance rates. Results from each Poisson regression model are found in *Table 3*. Overall, the risk scale and each corresponding subscale were predictive of program attendance. For the risk scale, and each subscale, higher scores were associated with lower attendance in the program. Individual risk appeared to be slightly more associated with increased absenteeism (*IRR* = 1.04, 95% CI [1.01, 1.07]). The overall risk scale (*IRR* = 1.03, *95% CI* [1.01, 1.05]) and environmental risk subscale (*IRR* = 1.03, 95% CI [1.01, 1.05] were associated with relatively similar risks of absenteeism from the program.

*Table 2*

*Logistic regression analysis of program dropout by risk type\**

|  | *Parameter* | *Estimate* | *OR* | *95% CI* | | *p* |
| --- | --- | --- | --- | --- | --- | --- |
| Model 1 | Intercept | -2.17 |  |  |  |  |
|  | All risk | 0.11 | 1.12 | 1.05 | 1.19 | <.01 |
|  | Male | -0.30 | 0.74 | 0.42 | 1.30 | .29 |
|  | Age (centered) | 0.24 | 1.28 | 1.09 | 1.50 | <.01 |
|  | White | 0.22 | 1.25 | 0.69 | 2.26 | .46 |
|  |  |  |  |  |  |  |
| Model 2 | Intercept | -1.76 |  |  |  |  |
|  | Environmental risk | 0.10 | 1.11 | 1.01 | 1.22 | .03 |
|  | Male | -0.30 | 0.74 | 0.42 | 1.29 | .29 |
|  | Age (centered) | 0.27 | 1.31 | 1.12 | 1.53 | <.01 |
|  | White | 0.21 | 1.23 | 0.68 | 2.21 | .49 |
|  |  |  |  |  |  |  |
| Model 3 | Intercept | -1.93 |  |  |  |  |
|  | Individual risk | 0.20 | 1.22 | 1.08 | 1.37 | <.01 |
|  | Male | -0.32 | 0.72 | 0.41 | 1.27 | .26 |
|  | Age (centered) | 0.21 | 1.23 | 1.04 | 1.45 | <.01 |
|  | White | 0.29 | 1.34 | 0.74 | 2.42 | .33 |

Note: \* Firth penalized likelihood models were regression models were run and showed similar results.

*Table 3*

*Poisson regression analysis of absenteeism by risk type*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | *Parameter* | *Estimate* | *IRR* | *95% CI* | | *p* |
| Model 4 | Intercept | -11.57 |  |  |  |  |
|  | All risk | 0.03 | 1.03 | 1.01 | 1.04 | <.01 |
|  | Male | 0.08 | 1.08 | 0.95 | 1.23 | .24 |
|  | Age (centered) | 0.07 | 1.07 | 1.03 | 1.11 | <.01 |
|  | White | 0.01 | 1.01 | 0.89 | 1.15 | .85 |
|  |  |  |  |  |  |  |
| Model 5 | Intercept | -11.51 |  |  |  |  |
|  | Environmental risk | 0.03 | 1.03 | 1.01 | 1.05 | .02 |
|  | Male | 0.09 | 1.09 | 0.96 | 1.24 | .20 |
|  | Age (centered) | 0.08 | 1.08 | 1.04 | 1.12 | <.01 |
|  | White | 0.02 | 1.02 | 0.89 | 1.16 | .77 |
|  |  |  |  |  |  |  |
| Model 6 | Intercept | -11.47 |  |  |  |  |
|  | Individual risk | 0.04 | 1.04 | 1.01 | 1.07 | <.01 |
|  | Male | 0.07 | 1.07 | 0.94 | 1.22 | .28 |
|  | Age (centered) | 0.06 | 1.06 | 1.03 | 1.10 | <.01 |
|  | White | -0.01 | 0.99 | 0.87 | 1.13 | .93 |

**Discussion**

Results support that scores on a standardized youth risk measure may be indicative of dropping out being absent from a youth intervention. Youth individual risk factors appear to be a more effective measure of predicting dropout and lack of attendance. Caretaker-reported internal conflicts are associated with risk of dropping out or being absent from the CC program. This is consistent with research showing maternal struggles increase dropout from youth service programs (Abrahamse et al., 2016). Results on individual risk factors are consistent with past research relating to at-risk youth and dropout in social programs (Borowsky, Taliaferro, & McMorris, 2013; Daniel et al., 2006). These results give indication that reasons for dropping out or being absent from an intervention may be in part due to a youth experiencing extraneous circumstances in their own life, thus preventing them from attending CC. Consistent with previous research, age is also a significant predictor of youth program dropout and absenteeism (Baruch et al., 2009; Mendenhall et al., 2014).

Result implications may be used to design interventions around composite and individual risk scores on the risk screening tool. The use of predictive models to help with participant dropout has already been used in school settings. (Gleason & Dynarski, 2002, 2017; Halawa, Greene, & Mitchell, 2014). These results may serve as generalizable to other at-risk youth service programs. Weiler, Boat & Haddock (2019) additionally found that the risk screening tool was associated relationship qualities between the youth and their associated mentors in the CC program. These finding may allow for a more tailored experience for youth, thus promoting not only increased program fidelity, but a better experience for youth. Other youth service programs may follow similar tailored approaches.

Our study promotes an applied approach to preventing youth program dropout and decrease absenteeism. Using a standardized risk measure, we propose an established typology for youth most likely to drop out and be absent from a program may be established. Prior to the start of an intervention, program staff may observe scores on this measure to identify youth at risk for dropout or higher rates of absenteeism. Once identified, program staff may intervene to prevent program dropout and absenteeism. Additionally, because the risk screening tool is heavily utilized in other youth service interventions (Weiler et al., 2019), implementation of this method highly practical.

Utilizing youth intervention staff members to identify and intervene on youth at higher risk may serve as a helpful strategy. Youth intervention staff already experience heavy burden when implementing evidence-based programs (Boustani et al., 2015). On top of this burden, it is also recognized that youth program staff are often not well-paid and only work part time (Huang et al., 2008). As a result, staff turnover in at-risk youth programs is high (Boustani et al., 2015). Rhodes (2004) expresses that a reduction in staff burden from youth dropout is ideal for ensuring program consistency and fidelity is ensured. A contributing factor to staff burnout is the work involved in trying to regain contact from youth that have already failed to attend program sessions. By providing strategies to prevent youth dropout, staff burden may be reduced.

Due to the extreme workload youth program staff members have (Boustani et al., 2015), it is important that the methods are quick and efficient. It is also imperative that staff identify youth whom are most likely to dropout or have high absenteeism prior to staff losing contact. Identifying dropout risk allows for early intervention by program staff. The earlier youth at higher risk for dropping out are identified, the sooner program staff may provide resources to ensure their stay in the program. Program staff may tackle this problem by providing resources to higher individual risk youth the resources to continue with the program. For example, weekly check-ups with higher risk youth may encourage continued participation in the program. Providing resources to youth, such as transportation services or increased emotional support to those who have higher risks may alleviate loss of contact from youth participants.

*Strengths and Limitations*

This study utilized a heavily controlled program with a relatively large sample to identify parameters associated with program dropout. Additionally, it provides multiple predictive models that go beyond looking at dropout or absenteeism in a singular fashion. We identify multiple facets of risk to provide a specific typology of youth at most risk for dropping out and being absent.

Limitations posed by this study include the potential lack of accuracy provided by caretaker report of adolescent risk. However, the Risk measurement has been heavily validated in its ability to identify youth risk in populations similar to CC (Herrera et al., 2013). This study only included individuals that began the program. It is possible that individuals that never began the program are characteristically different than those that were initially had the added effect of at least one session of the program.

The AUC ROC results indicated poor discriminability. Although the risk screening tool is associated with increased odds of dropping out of an adolescent intervention, accurately classifying youth that will dropout is not as plausible. Despite poor fit, the risk screening tool still has several advantages in being utilized in youth intervention programs. However, the pros outweigh the cons. Due to its commonality, it is still worth it to take note of these higher risk youth and provide them the resources to stay in the program via the risk screening tool.

*Future Studies*

Future research should apply the Risk measure to other programs focused on at-risk adolescent populations. By performing similar research on multiple communities, it will be possible to observe the generalizability of the measure to predict dropout across multiple communities. Incorporating similar measures in school systems may serve as useful. School dropout interventions are understood to be effective in community appropriate settings (S. J. Wilson, Tanner-Smith, Lipsey, Steinka-Fry, & Morrison, 2011). The use of a free standardized measure has the potential to be utilized across a diverse set of communities.

*Conclusions*

A standardized method allows for program staff to intervene on potential dropout youth prior to losing contact. Higher risk youth, the ones in most need of an intervention, may be provided more resources to encourage attendance to program services. Early intervention may promote increased program fidelity, which leads to increased program effects. Efforts aimed at keeping individuals within the CC program may be more efficient and beneficial as program staff have an extended opportunity to be proactive with these youth as they use the risk screening tool to intervene and directly during the program hours.

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