Preventing Drug Abuse Among Sexual Minority Youth

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Study Protocol

Background and Objectives:
Sexual minority youths' rates of drug use too often exceed those of their heterosexual peers. Sexual-minority adolescents are youth who self-identify as gay, lesbian, bisexual, or unsure of their sexual orientation. Sexual minority youth and heterosexual youth share many of the same risk factors, however, sexual minority youth have additional risk factors. Thus, tailored interventions to prevent sexual minority youth drug use are warranted.

This study developed and tested a web-based, prevention program aimed at addressing the general and specific risk factors for drug use among sexual minority youth in the United States. The goals of the study were:

1. Recruit a sample of sexual-minority youth, ages 15 & 16 years, from across the United States through online ads (e.g., Facebook, Instagram)
2. Develop and program a tailored, skills-based drug abuse prevention program for online delivery to sexual-minority youth; develop the attention-placebo website.
3. Deliver the prevention program to youth randomly assigned to the intervention arm; implement attention-placebo website procedures to youth randomly assigned to the control arm.
4. Test the efficacy of the prevention program to: a) prevent drug use, and b) reduce rates of drug use initiation at posttest and 1-, 2-, and 3-year follow-ups, relative to youth in the attention placebo control arm.
5. Test the efficacy of the program to change the mediators targeted in the intervention: skills related to goal setting, problem solving, drug refusal, and assertiveness; peer drug use; self-efficacy; normative beliefs; coping with stress; psychological distress; self-worth; and social supports at posttest and 1-, 2-, and 3-year follow-ups, relative to youth in the attention placebo control arm.

Study Design
The nationwide sample of 15- and 16-year-old youth (N = 1,216) was recruited via Instagram and Facebook. Enrolled youth were randomly assigned to the intervention or attention-placebo condition. All youth completed pretest measures online. Following pretest, intervention youth interacted with a 9-session, skills-based drug use prevention program online. The program aimed to reduce youths' drug use and associated risk factors by improving their cognitive and behavioral skills around such areas as coping with stressors, enhancing self-worth, and refusing drug use offers. Youth in both conditions completed measures at posttest, 1-, 2-, and 3-year follow-up. Youth received $25 for pretest, $30 for posttest, $35 for 1-year follow-up, $40 for 2-year follow-up and $50 for 3-year follow-up; each survey required approximately 15 minutes to complete.

Sample retention from baseline was 97% at posttest, 97% at 1-year follow-up, 95% at 2-year follow-up, and 96% at 3-year follow-up

Intervention
Following completion of the online pretest, youth in the intervention condition were directed to the online program, Free2b. The program consisted of two components: the homepage and the intervention sessions. The homepage for the program was accessible at any time and included extraneous, but potentially engaging, features, including: horoscopes, fortunes, quotes, lifehacks, popular LGBTQ+ icons, a quote of the day, and a resource page. Guided by social learning theory and minority stress theory (Fig. 2), the intervention consists of nine sessions: goal setting, decision making, self-esteem, coping with stress, reframing distorted thinking, two sessions on assertive communication, drug use knowledge and norms, and a review.

Youth assigned to the attention-placebo condition also had access to the Free2b website—identical to the website described above—but without the nine intervention sessions.

The 9-session intervention program was completed by 68% of youth; 3% of youth in the intervention arm completed zero sessions. On average, youth completed a session every 2.5 weeks, requiring an average of 23 weeks for all 9 sessions. During intervention delivery, the percent of youth who required additional reminders to complete the sessions varied from 33% (for session 3) to 1% (for session 9). Additional reminders were conducted via telephone, text, and social media direct messages.

Youth assigned to the attention-placebo arm also had access to a secure website—identical to the intervention website described above—but without the 9-session intervention. As intervention-arm youth were invited to participate with the intervention sessions, control-arm youth were similarly invited to access the attention-placebo website on the same delivery schedule as intervention-arm youth. All attention-placebo arm youth visited the site at least once. Specifically, 12% of youth visited only one time, 77% of youth visited 2 to 5 times, 9% of youth visited 6-9 times, and 2% of youth visited their site 10 or more times.

Statistical Analysis Plan

Data were cleaned and analyzed using R (R Core Team, 2024). 1201 cases constitute the analytic sample after three cases were removed for failure to complete the pretest measures and twelve cases were removed due to implausible extreme response patterns. Our approach to evaluating pretest comparability across groups involves hypothesis testing of independence or equality of means across treatment arms (e.g., chi-square tests for categorical demographics and two-sample t-tests for numeric risk factors). For numeric variables we also calculate standardized mean difference (Cohen, 1988) across groups, which gives the number of pooled standard deviations by which the group means differ. Values below 0.10 are considered acceptably balanced (Austin, 2009; Resa & Zubizarreta, 2016), while values between 0.10 and 0.25 are considered imbalanced but may be corrected by statistical adjustment (What Works Clearinghouse, 2022).

Drug use outcomes were recorded as past 30-day frequency counts. Count variables are not suitable as outcomes in OLS regression analyses because count variables are typically skewed to the right and have heteroskedastic errors. Poisson regression, in which the natural log of the count outcome is regressed on a linear combination of the predictors, is a sensible starting point for count outcome data. However, the validity of Poisson regression relies on the assumption that the conditional mean and variance of the count outcome are identical. In practice, this assumption is often violated; when it is, we say the Poisson model is “over-dispersed.” Negative binomial regression is an extension of Poisson regression that accounts for over-dispersion by permitting the conditional mean and variance of the outcome to differ (Hilbe, 2014).

After finding over-dispersion with Poisson regression models for drug use outcomes, we followed up by fitting negative binomial models in package MASS (Venables & Ripley, 2002). The negative binomial models fit the data better, as evidenced by likelihood ratio tests and the Bayesian information criterion (Schwarz, 1978). The impacts of the intervention on past-month drug use at posttest, 1-, 2-, and 3-year follow-up were analyzed via negative binomial models, controlling for pretest score, age, average letter grade in school, and parents’ education level.

In each model, we regress the outcome (past 30-day count) on treatment indicator (0 = control, 1 = intervention) and covariates, age (in years), average letter grade in school (1 = mostly A’s to 5 = mostly F’s), and parents’ education level (0 = less than 2 years of college, 1 = 2 or more years of college).

The impacts of the intervention on risk factors for drug use at posttest, 1-, 2-, and 3-year follow-up were analyzed via ordinary least squares multiple regression, controlling for pretest score, age, average letter grade in school, and parents’ education level.

References

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