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A Latent Transition Analysis of a Cluster Randomized Controlled Trial for Drug Use Prevention

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Objective: The objective of the study was to evaluate the impact of #Tamojunto, a Brazilian adaptation of the Unplugged prevention program, on patterns of drug use among adolescents and to characterize their trajectories of drug use over time. ***Method:*** An in-cluster randomized controlled trial was conducted in 2014–2015 with 2 parallel arms (intervention and control). The intervention group attended 12 weekly classes of the #Tamojunto intervention. The control schools did not offer a prevention program. The target population was students attending seventh and eighth grades. The primary dichotomous outcome measures were use of drugs (any alcohol use, binge drinking, tobacco, marijuana, inhalants, and cocaine) in the past year assessed using a questionnaire before intervention and in 2 waves of follow-up (9 and 21 months). ***Results:*** A latent transition analysis in 6,391 students from 72 public schools in 6 Brazilian cities revealed 3 distinct patterns of drug use behavior: abstainers/low users (81.54% at baseline, 70.61% after 21 months), alcohol users/binge drinkers (16.65% at baseline, 21.45% after 21 months), and polydrug users (1.80% at baseline, 7.92% after 21 months). No differences in the probabilities of transitions between these drug use patterns were found between the intervention and control groups. The most likely trajectory was no transition between patterns, regardless of the intervention and baseline pattern. ***Conclusions:*** The intervention was not successful in changing adolescent drug use patterns over time, showing that the components of the Brazilian adaptation of the Unplugged prevention program should be reevaluated.

What is the public health significance of this article?

This study suggests Brazilian adaptation of the Unplugged European school-based prevention program was not successful in changing adolescents' drug use patterns over time. Adolescents' drug use patterns were shown to be stable and have small changing probabilities over time. It implies that the initial drug use pattern commonly is preserved to subsequent evaluated moments. This study highlights the importance of rigorously evaluating the effectiveness of cultural adaptation version of evidence-based prevention programs to inform public policy.

Keywords: prevention, adolescence, drug use, randomized controlled trial, latent transition analysis

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All procedures in the use of human participants and/or animals in the present study were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki Declaration and its later amendments or comparable ethical standards.

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Unplugged is a school-based drug prevention program, based on the Model of Global Social Influence (Sussman, Stacy, Johnson, Pentz, & Robertson, 2004), which is intended to strengthen the personal and interpersonal skills of adolescents through interactive techniques and normative education (Kreeft et al., 2009). The social influence model assumes that drug use initiation results from social influences, through which adolescents develop erroneous perceptions of the frequency and acceptability of drug consumption (Giannotta, Vigna-Taglianti, Rosaria Galanti, Scatigna, & Faggiano, 2014). In a large multicenter randomized controlled trial of Unplugged in seven European countries, significant reductions in episodes of recent drunkenness and frequent cannabis use among adolescents were observed (Faggiano et al., 2010; Faggiano, Vigna-Taglianti, et al., 2008).

In Brazil, drug use has been identified as a major health concern in adolescents (Madruga et al., 2012; Pinsky, Sanches, Zaleski, Laranjeira, & Caetano, 2010), especially because the onset of drug use occurs early, between 12 and 14 years of age (Carlini et al., 2010; Malta et al., 2011). By the age of 14 years, 55.5% of adolescents have consumed alcoholic beverages, 21.4% reported episodes of drunkenness, 18.4% consumed tobacco, and 9% reported a lifetime use of any illicit drug (IBGE, 2016). Brazil has not historically implemented evidence-based drug use prevention programs in schools (Pereira, Paes, & Sanchez, 2016). To fill this gap, the national Ministry of Health conducted a transcultural adaptation and implementation of the Unplugged program, renamed #Tamojunto. The short-term goal of this program was to reduce the number of adolescents who experiment with and consume alcohol and other drugs (Faggiano, Galanti, et al., 2008). Because public policies should be supported by an evidence base that justifies national investment and expansion, it is necessary to assess the effectiveness of this program as implemented in Brazil.

Heterogeneity in the nature of adolescent drug use behavior has been described (Evans-Polce, Lanza, & Maggs, 2016), and patterns may cluster dynamically over time (Mistry et al., 2015). Statistical approaches that can characterize patterns of behaviors, and evaluate changes in behavioral patterns over time, have been applied to identify individuals who are at risk for drug use (Collins & Lanza, 2009). Latent transition analysis (LTA) assumes that a set of variables can be used to inform an underlying population structure, in which members of the same classes have common patterns of behaviors. LTA can be used to investigate how individuals transition from one latent class to another over time (Collins & Lanza, 2009). In a recent systematic review, most studies applying latent class approaches to drug use behavior identified four patterns: (a) no/low substance use; (b) alcohol use; (c) alcohol, tobacco, and marijuana use; and (d) polysubstance use (Tomczyk, Isensee, & Hanewinkel, 2016). That systematic review identified six drug use LTA studies, all of which examined adolescents in the United States, with one comparing the results of a U.S. and a Puerto Rican sample (Tomczyk et al., 2016). Of those studies that evaluated the probability of transitions between latent classes over the time, the most common scenarios involved remaining in the same class (Chung, Kim, Hipwell, & Stepp, 2013; Maldonado-Molina et al., 2007) or escalating to a polysubstance use class (Shin, Hong, & Wills, 2012).

The LTA approach offers powerful tools to estimate the probabilities of transitions from each substance use profile to the others over time (Lanza, Patrick, & Maggs, 2010), which is useful when testing intervention effects (Velicer, Martin, & Collins, 1996). This pattern-centered approach offers more qualified conclusions about the effects of an intervention compared with examining each behavior separately. It avoids blanket statements (Steinman & Schulenberg, 2003), and it provides greater statistical power for testing overall program effectiveness because it assesses changes in behavior patterns that underly individual observed indicators as opposed to performing multiple comparisons for multiple outcomes (Baldwin, 2015; Taylor, Graham, Cumsille, & Hansen, 2000). Despite these advantages, only a few studies have applied LTA to evaluate prevention programs (Graham, Collins, Wugalter, Chung, & Hansen, 1991; Spoth, Lopez Reyes, Redmond, & Shin, 1999; Strøm et al., 2014).

The current study advances two aims: (a) to evaluate the effectiveness of #Tamojunto, a Brazilian adaptation of the Unplugged prevention program, on drug use behavior over a 21-month follow-up period in early adolescence; and (b) to characterize the trajectories of early adolescent drug use patterns over time, evaluating the likelihood of change from previously observed behavior at 9 and 21 months. We hypothesized that the #Tamojunto prevention program would delay the onset of drug use and reduce the use of drugs; specifically, we aimed to show that the expected transitions between drug use patterns (i.e., an escalation in substance use behaviors over time) would be less likely among adolescents in the intervention condition compared with those in the control condition.

Method

Study Design

A 2-group, parallel-arm, school-clustered randomized controlled trial was conducted to compare the integration of the prevention program #Tamojunto into school curricula (intervention condition) with the usual curricula in Brazil, that is, no prevention program (control condition), among adolescents in public schools in six Brazilian cities (São Paulo, Federal District, São Bernardo do Campo, Florianópolis, Fortaleza, and Tubarão), located in four Brazilian states. The trial registration protocol at the Brazilian Register of Clinical Trials–REBEC, of the Brazilian Federal Government, is RBR-4mnv5*g*.

The target population was students attending seventh and eighth grades (12–13 years of age) in the participating cities. Selection of the age group was based on the feasibility of a 2-year follow-up during compulsory middle school attendance. From the sample universe of all public schools in the participating cities (according to the national registration list of schools from the Instituto Nacional de Estudos e Pesquisas Educacionais Anísio Teixeira), 72 schools were randomly selected, proportional to the number of schools in the municipality (stratum). Among the schools selected to participate in the study, a second allocation determined whether each school would be assigned to the control or intervention group according to a random list, maintaining a 1:1 allocation ratio per municipality. Randomization was performed at the school level, via the Excel macro [command RAND].

In the intervention schools, students received 12 lessons of the #Tamojunto program substituted in place of a normal curriculum, whereas the control schools did not implement any prevention program. No other prevention programs were implemented simultaneously in any of the participating schools. The cultural adaptation and implementation of the program were responsibilities of the Brazilian Ministry of Health (BMH). Evaluation was conducted by independent researchers.

Data were collected simultaneously in the control and intervention schools at three time points (see Figure 1). The first follow-up was collected at the end of the school year to avoid likely loss to follow-up because of summer vacation. Consent to participate in the study was obtained from all of the school directors, teachers, and student participants. All participants took part voluntarily after informed consent, based on the principle of adolescent autonomy under the Brazilian Statute of Children and Adolescents (Law No. 8969/1990). This study was approved by the Ethics in Research Committees at the University of São Paulo (#473.498) and the Federal University of Santa Catarina (#711.377).

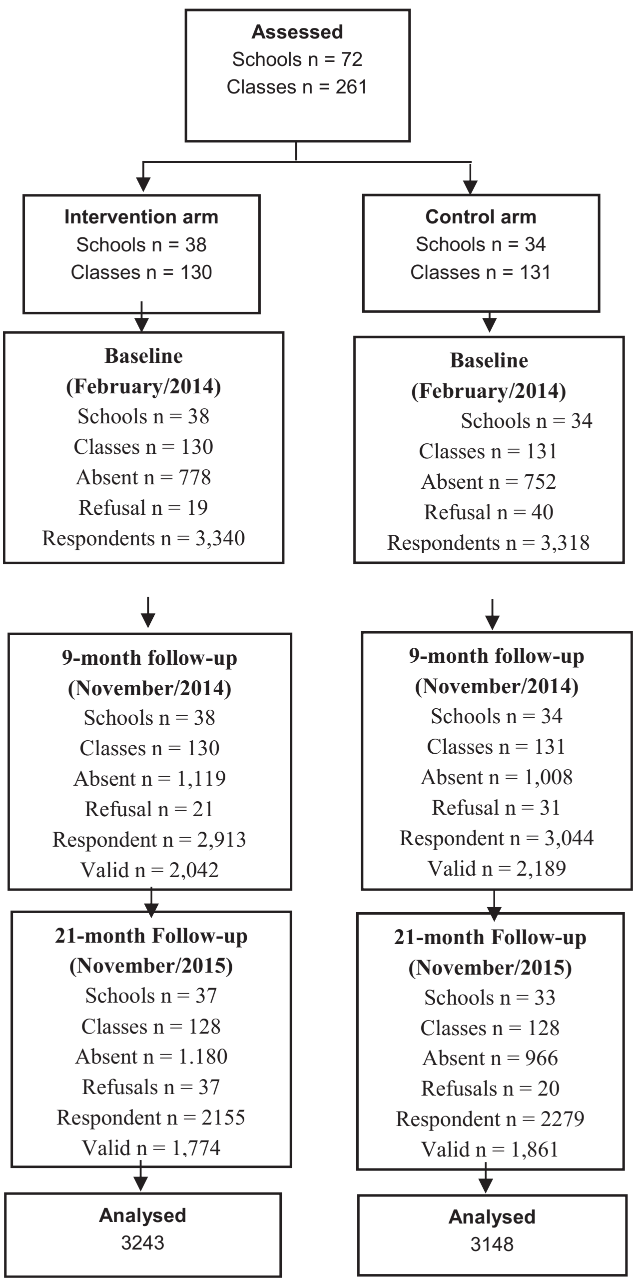

Figure 1. CONSORT flow diagram for the randomized controlled trial. Absent = absent from school in moment of the assessment; refusals = subjects who refused to participate in the assessment; valid = number of subjects used in the cross-sectional latent class analysis; respondent = participants assenting to participate, providing data.

Population and Sample Size

Based on the sample size calculation (Lwanga, Lemeshow, & World Health Organization) to achieve a power of 80%, a significance level of 5% for a difference between groups of 1.5 percentage points (e.g., from 5% to 3.5%), the necessary sample size for each study arm was calculated to be 2,835, in a ratio of 1:1. To account for losses to follow-up and for a high intraclass correlation, the sample was increased by 50% to a recruitment target of 4,253 participants in each arm. The parameters used were based on a previously conducted pilot study, and historical school absence rate data (Sanchez et al., 2016).

Because the target population was 13-year-old students (enrolled in eighth grade) and because each school had approximately four eighth-grade classes of 30 students each, at least 35 schools in the intervention arm and the same number in the control arm (total of 70 schools) were needed to achieve the number of students required. Considering a 10% refusal of schools, 38 schools were enrolled in each arm. In each of the participating municipalities, four to 30 schools were randomly selected (in proportion to the size of the city's population).

In each of the schools, all eighth-grade classes were invited to participate in the study prior to randomization of groups. In Fortaleza, Santa Catarina, and Tubarão, the seventh-grade classes of the selected schools were also included because these cities were in the process of changing the age of students assigned to each grade.

Intervention

The Unplugged program was first designed by the European Drug Addiction Prevention Trial (EU-DAP) group (Kreeft et al., 2009), and it consists of 12 classes (four 1-hr classes on attitudes and knowledge about drugs, four classes on social and interpersonal skills, and four classes on personal skills) with on average 50 min, applied to students by teachers trained and guided by the student and teacher manuals. Both manuals are open access and made available in several languages on the website www.eudap.net.

The BMH team performed the translation and transcultural adaptation of the program under supervision of the European developers, in 2013. The English version of the Unplugged material was translated into Portuguese, retaining the original format and subjects (educational strategies provided in 12 classes and three parent workshops) but with adapted activities. Given the epidemiological profile of illegal drug use among students in Brazil, information on heroin was replaced with information on crack-cocaine (Carlini et al., 2010). Further details of the cultural adaptation process are described elsewhere (Abreu et al., 2017).

The teachers who delivered the program attended a 16-hr training facilitated by coaches trained by the European developers, the master-trainers of the EU-DAP Intervention Planning Group (Gabrhelik et al., 2012). At the end of each class, teachers completed a fidelity questionnaire to assess the dose of the program delivered. To guarantee fidelity and dose, teachers were supervised monthly by the coaches from the BMH who had facilitated the initial training.

Instrument and Variables

The instrument used for data collection was developed, tested, and implemented previously by the EU-DAP (Faggiano, Vigna-Taglianti, et al., 2008). In Brazil, we used an adapted version of the questionnaire translated into Portuguese (Cainelli et al., 2016). The questionnaire evaluates a set of variables including sociodemographic data and past-month (yes/no) and past-year (yes/no) use of alcohol, tobacco, marijuana, inhalants, cocaine, and crack. It also evaluates the practice of binge drinking (the consumption of five or more alcoholic drinks on a single occasion) in the past month and past year. Socioeconomic status (SES) was assessed using the scale from the Brazilian Association of Research Companies (ABEP, 2012). The outcomes analyzed were past-year use of alcohol, tobacco, marijuana, inhalants, and binge drinking at the three time points (baseline, 9 months after, and 21 months after the baseline).

To pair (link) the questionnaires of each subject, students filled in a secret code involving letters and numbers created from their first name, surname, date of birth, mother's name, father's name, and maternal grandmother's name. Each code was composed of eight characters (seven letters and one number), which could be decoded only by the students themselves. These codes allow researchers to link individual questionnaires at different times of the study while protecting the anonymity and confidentiality of the participants (Galanti et al., 2007). The secret codes were matched using the Levenshtein algorithm, which identifies similarities among a set of characters. School and class codes were included in the matching process (Levenshtein, 1965). Questionnaires that were positive for lifetime use of a fictional drug (Holoten or Carpinol) were excluded from the analysis.

Statistical Analysis

LTA, a longitudinal extension of latent class analysis involving multiple latent class variables, was used to evaluate the effectiveness of the intervention on the probabilities of transitioning between drug use patterns (Nylund, 2007). LTA characterizes drug use patterns within each wave and identifies the probabilities of transitions between them from one wave to the next. Robust maximum likelihood estimation was used under full information maximum likelihood (FIML) and the assumption of a missing at random mechanism, subverting the need to impute missing data. Because of the nested structure of the data (i.e., individual adolescents nested within 72 schools), the standard errors and χ^2 test of the model fit took into account nonindependence (Asparouhov, 2005, 2006).

To test whether transitional probabilities from baseline to 9 months and from 9 to 21 months were all significantly different from zero between groups, an omnibus (Wald) test was used. This is a formal omnibus test comparing all the same pattern of class transitional probabilities between #Tamojunto and control within each adjacent period (e.g., four logits coming from baseline to 9 months and four logits from 9 to 21 months). The statistical significance level was $p =$ .05. All analyses were run in Mplus version 7.4 (Muthén & Muthén, 2010) and outputs are available upon request.

The extraction of latent classes ceased when the inclusion of a class yielded little additional information. The model was adjusted based on the goodness-of-fit criterion and took into consideration the parsimony and interpretability of the classes; that is, in addition to the statistical indices presented below, the decision about the best solution and number of latent classes took into consideration the most consistent statistical and conceptual distinctions among the groups. The following fit indices were used to decide statistically the best solution: the Akaike information criterion; the Bayesian information criterion (BIC); the sample size–adjusted Bayesian information criterion (SSABIC); and the Vuong-Lo-Mendell-Rubin test (VLMR). Finally, to assess how well discriminated the latent classes underlying the best solution were, we used entropy, which is based on an a posteriori probability and indicates the accuracy of the classification; values close to 1 indicate clear and very precise classifications. We emphasize that entropy, in itself, was not used to decide the best solution for the number of latent classes.

Because FIML assumes a missing at-random mechanism, in which data are missing completely at random in relation to other variables, the following covariates were included in the model: sex, age, SES, and group assignment at the individual level. The outcomes were modeled conditional on covariates and the covariates have no distributional assumptions. For missing data, the standard errors of the parameter estimates are computed using the observed, rather than the expected, information matrix (Kenward & Molenberghs, 1998). In short, covariates were included to support the missing at random approximation under FIML.

Given that LTA assumes local independence of class indicators, we also tested the bivariate residuals to rule out dependence, in which values higher than 1.96 would indicate lack of local independence (Reboussin, Ip, & Wolfson, 2008).

Results

Participants

A total of 72 schools accepted our invitation to participate in the study, as described in Figure 1, and school characteristics were similar between groups (Supplemental Table 1). Table 1 shows the distribution of students' sociodemographic data and the frequency of five indicators of drug use within the three waves and the percentage of missing data by group. The intervention was offered March through June 2014. A total of 89% of the classes received the complete program (12 lessons); the other 11% discontinued the program between lessons 4 and 11. Questionnaires endorsing use of a fictional drug were excluded from the analysis ($n = 49$ at baseline, $n = 70$ at 9 months, and $n = 25$ at 21 months).

Class Enumeration (Cross-Sectional)

In each wave, a total of five classes were defined. Table 2 shows values of the information criteria. In Wave 1, a higher BIC value suggested that the three-class model was slightly superior to the others, whereas the SSABIC value and the VLMR and Lo-Mendell-Rubin test (LMR) favored the four-class model. In Wave 2, the fit indices (lower BIC, SSABIC and Akaike information

Table 1
Proportion of Past-Year Drug use in the Intervention and Control Groups Across Time (n = 6,391)

Variables	Control		Experimental	
	n (%)	Missing (%)	*n* (%)	Missing (%)
Baseline				
Gender		—		—
Boys	1,530 (48.6%)		1,600 (49.3%)	
Girls	1,618 (51.4%)		1,643 (50.7%)	
Age, years		—		—
11–12	1,700 (54%)		1,643 (50.7%)	
13–14	1,448 (46%)		1,600 (49.3%)	
SES		7 (.22%)		8 (.25%)
A	119 (3.8%)		125 (3.8%)	
B	1,206 (38.3%)		1,261 (38.9%)	
C	1,639 (52.1%)		1,704 (52.5%)	
D/E	177 (5.62%)		145(4.5%)	
Past-year drug use				
Alcohol	1001 (31.8%)	21 (.7%)	1014 (31.3%)	26 (.8%)
Binge drinking	487 (15.5%)	28 (.9%)	519 (16.0%)	42 (1.3%)
Tobacco	115 (3.7%)	28 (.9%)	128 (3.9%)	35 (1.1.%)
Inhalants	254 (8.1%)	27 (.9%)	271 (8.4%)	37 (1.1%)
Cannabis	73 (2.3%)	25 (.8%)	83 (2.6%)	39 (1.2%)
9 months				
Past-year drug use				
Alcohol	731 (23.2%)	977 (31%)	761 (23.5%)	1,211 (37.3%)
Binge drinking	353 (11.2%)	981 (31.2%)	373 (11.5%)	2,016 (62.2%)
Tobacco	111 (3.5%)	976 (31.0%)	105 (3.2%)	1,224 (37.7%)
Inhalants	237 (7.5%)	976 (31.%)	185 (5.7%)	2,018 (62.2%)
	94 (3.0%)	976 (31.%)	108 (3.3%)	2,026 (62.5%)
21 months				
Past-year drug use				
Alcohol	849 (27.05)	1,294 (41.1%)	882 (27.2%)	1,472 (45.4%)
Binge drinking	460 (14.6%)	1,304 (41.45)	448 (13.8%)	1,760 (54.3%)
Tobacco	122 (3.9%)	1,302 (41.4%)	130 (4.0%)	1,484 (45.8%)
Inhalants	202 (6.4%)	1,845 (58.6%)	175 (5.4%)	1,764 (54.4%)
Cannabis	133 (4.2%)	1,302 (41.4%)	143 (4.4.%)	1,489 (45.9%)

criterion values, and VLMR and LMR statistic significant) suggested that the four-class model was slightly superior to the others. However, examination of the four-class solution in Waves 1 and 2 led us to select the three-class model because it was the most coherent on the balance of theoretical and mode fit criteria. The fourth class, a subgroup of the polydrug users who did not consume alcohol, accounted for a very small proportion of subjects (0.25–0.52%), which did not satisfy the recommendation that a valid class should contain not less than 5% of the sample (Nagin, 2005). For the three-class solution, the entropy values were 0.89 and 0.85 in Waves 1 and 2, respectively. In Wave 3, the BIC value and the VLMR and LMR tests favored the three-class model, whereas only the SSABIC favored the four-class model. For the three-class solution, the value of entropy was 0.82. Taking the BIC as one of the most reliable measures (Nylund, Asparouhov, & Muthén, 2007) and the small proportion of subjects in the fourth class (0.25%), the model with three latent classes was also chosen as the most parsimonious in Wave 3. Therefore, for each of the three waves, the best model solution identified three latent classes based on a combination of theoretical and model fit criteria (Marsh, Lüdtke, Trautwein, & Morin, 2009). The three classes distinguished polydrug users, alcohol users/binge drinkers, and abstainers/low users. For each wave, the class memberships are enumerated in Supplemental Table 2.

Adolescents classified as polydrug users exhibited the highest probabilities to have used all five drugs. Those classified as alcohol users/binge drinkers had high probabilities to endorse alcohol use and binge drinking in the past year; however, they had lower probabilities to endorse use of cannabis, cigarettes, and inhalants. The third class exhibited very low probabilities of alcohol use, binge drinking, and use of tobacco or cannabis; however, there was a small probability for isolated use of alcohol (12.4%) or inhalants (4.7%) in this class (see Supplemental Figure 1 in online supplemental material).

The relative proportions of the classes were relatively stable across the waves. That is, the polydrug user class was consistently the smallest (from 1.8% to 7.8%), the alcohol users/binge drinkers comprised the next smallest (from 16.6% to 29.4%), and the abstainers/low users class comprised the largest (from 64.4% to 81.5%).

The results of the bivariate residuals test showed that the assumption of local independence of class indicators at the three waves held. This was conducted via inspection of the standardized residuals, which ranged from −0.012 to 0.018 at Wave 1, −0.003 to 0.003 at Wave 2, and −0.003 to 0.003 at Wave 3.

Invariance Testing and Longitudinal Findings

Regarding invariance, the log likelihood ratio test comparing full invariance and full noninvariance models was not statistically

Table 2
Probability of Transition Between Classes From Baseline to 9 Months and from 9 Months to 21 Months in Control and Intervention Arms

	9 months					21 months		
	Polydrug users	Alcohol users/binge drinkers	Abstainers/ low users			Polydrug users	Alcohol users/binge drinkers	Abstainers/ low users
				Control				
Baseline								
Polydrug users	.808	.087	.105		Polydrug users	.760	.087	.153
Alcohol users/binge drinkers	.139	.570	.291	9 months	Alcohol users/binge drinkers	.164	.708	.128
Abstainers/low users	.031	.135	.834		Abstainers/low users	.031	.216	.753
				#Tamojunto				
Baseline								
Polydrug users	.880	.053	.067		Polydrug users	.878	.066	.056
Alcohol users/binge drinkers	.108	.629	.263	9 months	Alcohol users/binge drinkers	.144	.673	.184
Abstainers/low users	.033	.170	.797		Abstainers/low users	.032	.249	.719

significant ($\chi^2_{[30]} = 2.35$, $p = .999$), indicating that the class solutions are stable across time, consistent with visual inspection of the cross-sectional drug profile plots (Supplemental Figure 1).

Table 2 describes the movement of individuals into and out of the drug use behavior classes, allowing comparison of transition probabilities over time (i.e., baseline to 9 months and 9 months to 21 months). There were no significant differences in transition probabilities between the intervention and control groups ($\text{Wald}_{[8]} = 8.700$, $p = .3683$), controlling for age, sex, and SES. For example, the probability that an individual who was a polydrug user at baseline remained in this class after 9 months was 0.808 for the control group and 0.880 for the intervention group. The probability to remain in the same drug behavior class at the adjacent time was the highest observed for each baseline behavior patterns (along the diagonal axis in Table 2). The off-diagonal values (see Table 2) describe movement between the classes over time. Numerically, the highest probability of transition occurred among those who began the study as alcohol users/binge drinkers; after 9 months 29.1% of those in the control group and 26.3% of those in the intervention group became abstainers/low users. After 21 months, the highest probability of transition from one class to another was among those who were abstainers/low users at 9 months and become alcohol users/binge drinkers by 21 months, representing 21.6% in the control group and 24.9% in the intervention group.

Table 3 shows the effects of the intervention on class membership over time. At baseline there was no increased likelihood in the intervention arm to be a polydrug user ($\beta = -0.042$, $p = .851$) or a alcohol users/binge drinkers ($\beta = 0.035$, $p = .720$), indicating no difference in the class composition entering the trial between the study arms. Moreover, the three-class solution was invariant across the arms at baseline, indicating that the probabilities to endorse yes

Table 3
Logistic Regression Coefficients for Time-Varying Intervention Effect in an LTA Model With Nonstationary Transitions

Classes[a]	Effect[b]	Coefficent	*SE*	*p* value	Odds ratio	95% CI
Polydrug users (baseline)	#Tamojunto	−.042	.226	.851	.958	[.61, 1.49]
Alcohol users/binge drinkers (baseline)	#Tamojunto	.035	.098	.720	1.035	[.85, 1.25]
Polydrug use (9 months)	#Tamojunto	−.105	.318	.742	.900	[.48, 1.67]
Sex[c]		.268	.160	.094	1.300	[.95, 1.78]
Age		.417	.128	.001	1.517	[1.18, 1.95]
SES		.000	.010	.985	1.000	[1.18, 1.95]
Alcohol users/binge drinkers (9 months)	#Tamojunto	−.277	.146	.058	.758	[.56, 1.00]
Sex		.462	.091	<.0001	1.587	[1.32, 1.89]
Age		.153	.066	.02	1.160	[1.02, 1.32]
SES		.012	.006	.066	1.012	[1.00, 1.02]
Polydrug users (21 months)	#Tamojunto	−.067	.386	.862	.935	[.43, 1.99]
Sex		.312	.163	.056	1.366	[.99, 1.88]
Age		−.048	.100	.623	.952	[.78, 1.15]
SES		.012	.012	.312	1.010	[.98, 1.03]
Alcohol users/binge drinkers (21 months)	#Tamojunto	−.191	.123	.120	.826	[.64, 1.05]
Sex		.439	.078	<.0001	1.550	[1.33, 1.80]
Age		.045	.061	.464	1.046	[.92, 1.17]
SES		.022	.007	.001	1.022	[1.00, 1.03]

Note. CI = confidence interval.
[a] Abstainers/low users is the reference. [b] Control group is the reference. [c] Sex and age at baseline are the reference.
Adjusted for age, sex, and SES.

for any of the five indicators were no different between the control and intervention groups. At 9 months and 21 months, there were no differences in the likelihood of being in any particular drug use class based on randomization to #Tamojunto, indicating that the intervention exerted no significant effects on patterns of drug use.

Post Hoc Power Calculation

In terms of power, as per Baldwin (2015), we conducted a Monte Carlo simulation to evaluate the power to identify the transitional probabilities using the observed estimates (item probabilities across classes and times) for a sample size of $n = 6{,}391$ under 10,000 replications. The eight logit transition probabilities were estimated per group (intervention vs. control). Twelve of the 16 transition probabilities achieved power greater than 0.8 (data available upon request). The four transitional probabilities with power <0.8 involved changing from polydrug users to binge drinking (power to predict transition from polydrug users at baseline to binge drinking at 9 months was 69% in the control group and 49% in the intervention group).

Discussion

This study evaluated the effectiveness of a universal program on changing drug use behavior among adolescent students. Although some studies have examined the patterns of substance use trajectories (Chung et al., 2013; Lanza et al., 2010; Shin, Lee, Lu, & Hecht, 2016), little is known about how prevention programs might affect transitions between substance use profiles (Dielman, 1994; Spoth et al., 1999). The present study describes a pattern-centered approach for evaluating substance use prevention programs in an attempt to bridge the gap between developmental theory and prevention practices (Steinman & Schulenberg, 2003).

The main result is a lack of effect of the intervention on the probability of belonging to a given class of substance use. #Tamojunto did not delay the onset of drug use or reduce drug use behavior because the escalation in substance use behaviors was similar over time in the intervention group and the control group. Most of the students maintained their pattern of drug use, regardless of their allocated group over 21 months of follow-up. The finding differs from the positive results from the Unplugged program in Europe (Faggiano et al., 2010; Faggiano, Vigna-Taglianti, et al., 2008); however, that evaluation focused on differences in change over time in the use of individual substances separately, which assumes independence of the outcomes without considering the interdependence of drug use behaviors that indicate underlying heterogeneity among adolescents. Because these patterns cannot be accounted for by correcting for multiple comparisons to account for false discovery rate, an LTA approach may be preferable.

Three classes of drug use behavior were identified: polydrug users (1.8–7.8%), alcohol users/binge drinkers (16.65–29.42%), and abstainers/low users (64.4– 81.5%). The findings are consistent with those of a recent systematic review, which found that the class of abstainers/low users was usually the largest class, the class of polydrug users was the smallest class, and the intermediate classes were usually intended to identify the use of isolated substances or other patterns such as binge drinkers (Tomczyk et al., 2016). Two other studies identified three similar latent class structures as the best models to understand patterns of drug use by adolescents: one in Australian youth (Kelly et al., 2015) and the other in American girls (Chung et al., 2013).

We report a general stability regarding drug use behaviors from baseline to 9 months and from 9 months to 21 months. For example, the adolescents classified as abstainers/low users were most likely to remain in this category, with much lower probability to move to a polydrug user profile, and this was independent of receiving the intervention. This result was in accordance with recent studies, which showed that the highest probability among transition alternatives was remaining in the same latent class and not to progress further (Baggio et al., 2014; Patrick et al., 2009). As expected, the prevalence of polydrug users and alcohol users/binge drinkers increased numerically over 21 months, whereas the proportion of abstainers/low users decreased similarly in both the intervention and control arms.

Because a null effect of the intervention was observed, the implementation of the intervention and its components should be evaluated. One potential alternative approach would be to consider implementing selective programs as opposed to a universal program. The possible advantages of selective programs have been discussed recently, with several positive studies highlighting effectiveness (Conrod, 2016; Shetgiri, Kataoka, Lin, & Flores, 2011). Based on the current analysis, discreet drug use profiles can be identified, and selective approaches targeting these specific profiles would be one possible approach (Offord, 2000).

The results emphasize the importance of rigorously evaluating the effectiveness of prevention programs to inform public policy (UNODC, 2015). Specifically, they highlight the importance of cultural considerations in adapting drug prevention interventions across sociogeographical landscapes (Barrera, Berkel, & Castro, 2017).

Attrition is an expected limitation in randomized trials, especially among those with long follow-up. LTA estimates under full-information maximum likelihood offer solutions to these missing data problems. The lowest coverage covariance was 0.44 among drug indicators from the second and third waves, indicating that 44% of the data are present (see Supplemental Table 3). Moreover, although data for those who have information at only one of the three waves do not contribute to the estimation of the transition parameters, they do contribute to estimating the time-specific parameters, helping to provide estimates that are more accurate and in compliance with intention-to-treat analytical paradigm (Moher, Schulz, & Altman, 2001).

Although the intervention showed a lack of evidence for the effect of treatment on transitions between behavior patterns, baseline patterns of drug use appeared to have been balanced between the trial arms, suggesting low risk of bias. In terms of power, our Monte Carlo simulation suggested adequate power to identify all common transitions, with power <0.8 observed only for four uncommon transitions involving escalation patterns that were not the target of treatment a priori (e.g., switching from polydrug use to binge drinking). Although there was an overlap of 3 months in the baseline and 9-month data for the last-year drug use, there was no overlap in the 21-month follow-up period, and the proportions in each class were consistent between the two follow-up timepoints. If a true effect of the program over 9 months was not observed because of partial overlap with baseline data, that effect was not relevant in a 9- to 21-month period after baseline. Additionally, if we consider only assessments at baseline 21 months, no transition probabilities differed between groups ($Wald_{[4]} = 2.261$, $p = .688$, with $p > .05$ for all probabilities of transitions between groups). Another potential limitation is that the control group should have been exposed to the same procedures (albeit not the intervention) as the experimental group; however, this does not invalidate a negative finding. Moreover, the prevention program replaced other curricular elements to maintain consistent time in class, attention to students, and so forth between study arms.

Conclusion

The latent transition analysis approach identified three common drug use patterns in this large Brazilian sample. Because this is the first application of latent transition analysis to patterns of drug use behavior in a randomized controlled trial, future studies might explore the impact of interventions on transitions between other latent class structures based on these and additional indicators of drug use. Transition probabilities in drug use patterns were relatively uncommon over time, and they were not influenced by the intervention. In terms of local policy, the null effect of this intervention suggests that the #Tamojunto program components might be reevaluated before attempting broad, national expansion.

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