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Original article

U.S. Trends in Adolescent Substance Use and Conduct Problems and Their Relation to Trends in Unstructured In-Person Socializing With Peers

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A B S T R A C T

Purpose: This study examined whether national trends in unstructured in-person socializing with peers (i.e., socializing without goals or supervision) among adolescents could help explain recent declines in adolescent risk behaviors (e.g., substance use, fighting, theft).
Methods: The sample contained of 44,842 U.S. 12th-grade students (aged 17–18 years) from the Monitoring the Future survey (years 1999–2017). Analyses examined (1) prevalence trends, (2) latent factor structure of risk behaviors and unstructured in-person socializing, and (3) whether trends in the unstructured in-person socializing factor accounted for the relationship between time (i.e., survey year) and the risk behavior factor.
Results: Adolescent risk behaviors and unstructured in-person socializing declined by approximately 30% in the U.S., and both formed coherent latent factors. After adjusting for sociodemographics, declines in unstructured in-person socializing accounted for approximately 86% of declines in risk behaviors.
Conclusions: The prevalence of risk behaviors and unstructured in-person socializing behaviors declined among U.S. 12th graders from 1999 to 2017. It is unknown whether such effects are directly causal and/or influenced by unmeasured variables. However, the results provide evidence that national declines in unstructured in-person socializing are a likely component of the explanation for national declines in adolescent risk behaviors.

IMPLICATIONS AND CONTRIBUTION

This study demonstrates a robust statistical link between declines in unstructured in-person socializing and risk behaviors among U.S. 12th graders from 1999 to 2017. Although the results do not establish a direct causal relationship, they imply that explanations for risk behavior trends need to also account for unstructured in-person socializing trends.

Adolescent behavior in the U.S. and other western countries has changed substantially over the past two decades. Multiple epidemiological studies demonstrate that youth are now significantly less likely to engage in risk behaviors (RBs), such as substance use, conduct problems (e.g., fighting and stealing), and early sexual activity. For example, several alcohol use behaviors

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(e.g., any past-month drinking and binge drinking, past-month frequency of drinking) declined among adolescents by approximately 5%–20% during the first decade of the 2000s across much of North America, Europe, and Australasia [1–4]. Similar declines have been observed for tobacco, cannabis, and illicit drugs [5–7] as well as sexual activity [8] and conduct problems [5,9].

In the developmental psychology literature, problem behavior theory (PBT) [10] demonstrates that the co-occurrence of substance use, conduct problems, and early sexual activity can be modeled as a single latent variable that can predict patterns of *multiple* forms of behavior among youth [10,11]. In other words, it may be more useful to examine the covariance among these behaviors as a single underlying trait rather than studying each behavior in isolation. Using PBT as a theoretical foundation, recent analyses demonstrate that RBs cluster within youth in a similar fashion across multiple countries [12,13]. Moreover, population-level declines in RBs might be better described as a decrease in the underlying propensity toward all these behaviors, rather than as contemporaneous but independent declines in individual behaviors [14–16]. This suggests that explanations for declines in RBs should be able to account for trends in multiple behaviors rather than only invoking behavior-specific explanations (e.g., youth tobacco policies).

PBT also provides a psychosocial framework for understanding the impact of various person- and environmental-level variables on RB susceptibility [10,11]. For example, poverty, school quality, and parental oversight all contribute to the balance of factors that influence adolescent RBs. One critical variable that contributes to this balance is social context [17]. Specifically, PBT suggests that to understand the occurrence and maintenance of adolescent RBs, one must understand the "…social ecology of adolescent life," which "…provides socially organized opportunities to learn RBs together and normative expectations that they be performed together." [17].

However, social context is a difficult concept to operationalize. Youth's "social ecology" is comprised of multiple unique social situations that change from hour-to-hour and day-to-day. Thus, determining if and how RBs are related to social context requires that we identify specific *types* of social contexts. To address this, we turn to the concept of unstructured in-person socializing (UIS) [18]. This framework posits that RBs can emerge when youth are placed in situations with three characteristics: (1) presence of peers (2) lack of authority figure(s), and (3) no set agenda, goal, or activity [18]. There is significant evidence that youth who are consistently exposed to situations with these characteristics are more likely to engage in RBs [19,20].

If UIS is a strong predictor of RBs, then it is prudent to examine whether national trends in UIS are associated with recent national trends in RBs [21,22]. The results from a recent study point toward this possibility. From 2002 to 2010, youth from multiple countries became significantly less likely to report socializing in person with friends every night of the week, and countries that underwent the largest decline in substance use also underwent the largest decline in face-to-face contact with peers [16]. The aim of the present study was to expand on this work by using nationally (U.S.) representative survey data on youth behavior to examine two questions: (1) Has the prevalence of UIS declined among U.S. adolescents? (2) Do trends in UIS statistically explain trends in adolescent RBs? Although such an analysis cannot prove a direct causal relationship between UIS and RBs, a strong association between the trends in these behaviors would indicate overlapping causal explanations.

Methods

Survey

Monitoring the Future (MTF) is a nationally representative annual cross-sectional survey of U.S. 12th-, 10th-, and eighth-grade students (aged 18–17, 16–15, and 13–14 years, respectively). The present study used only the 12th-grade sample because assessments of relevant behaviors were less extensive in eighth- and 10th-grade samples. MTF samples from approximately 130 schools using multistage random sampling. Survey administration follows a structured protocol, and approximately 75%–80% of questionnaires are completed. MTF distributes different questionnaires (i.e., "Forms") containing universal questions and questions unique to specific forms [23]. In this study, only "Form Two" data were analyzed because this form contained the necessary items. Our university institutional review board determined that this research was exempt from review because the data are deidentified and publicly accessible.

RB factor indicator variables

To calculate prevalence estimates and annual percent change, we used dichotomized (yes or no) versions of nine RBs: past 30-day use of (1) alcohol (2) cigarettes (3) cannabis (4) cocaine; and past-year (5) fight at school (6) hurt someone on purpose (7) threaten someone with a weapon, (8) steal something worth <$50, and (9) steal something worth ≥$50. These variables were selected based on PBT [11]. We conducted sensitivity analyses using the original, multicategory response option versions of these variables (Appendix A).

UIS factor indicator variables

UIS was assessed with the four items originally used to develop the concept of unstructured socializing [18]. These items assessed past-year frequency of (1) going out for fun in the evening (during a typical week), (2) going to parties, (3) riding around in a car for fun, and (4) getting together with friends. Response options for item 1 were "less than one," "one," "two," "three," "four or five," and "six or seven." Response options for items 2–4 were "never," "a few times a year," "once or twice a month," "at least once a week," and "almost every day." To remain consistent with the recoding of RBs, we dichotomized UIS variables at the approximate 50th percentile of the full sample distribution (Table 1). As with the RB construct, we conducted sensitivity analyses using the original, multicategory response option versions of these variables (Appendix A).

Sociodemographics

Sociodemographic covariates included (1) lives with mother and/or father, (2) parents have a college education or higher, (3) mother employment status (father employment status was not available), (4) number of siblings, (5) race, and (6) urbanicity of living environment. Age and gender were not considered because the MTF sampling design ensures that the distribution of these variables remains the same each year.

Table 1
Relative annual change in the prevalence of risk behaviors and unstructured in-person socializing behaviors among U.S. 12th graders (Monitoring the Future survey: 1999–2017)

	APC[a]	(95% CI)	Prevalence: 1999 versus 2017			
			Year: 1999	(95% CI)	Year: 2017	(95% CI)
Risk behaviors						
Used alcohol (past 30 days)	−2.2%	(−2.4%, −2.0%)	51.0%	(48.5%, 53.4%)	34.4%	(32.1%, 36.9%)
Used cigarette (past 30 days)	−5.7%	(−6.1%, −5.3%)	35.3%	(33.0%, 37.6%)	9.7%	(8.3%, 11.3%)
Used cannabis (past 30 days)	.3%	(−.1%, .7%)	24.4%	(22.4%, 26.6%)	23.6%	(21.6%, 25.7%)
Used cocaine (past 30 days)	−6.0%	(−7.4%, −4.5%)	2.3%	(1.7%, 3.2%)	.9%	(.6%, 1.4%)
In physical fight (past year)	−2.1%	(−2.6%, −1.5%)	14.7%	(13.1%, 16.5%)	10.5%	(9.0%, 12.1%)
Hurt someone on purpose (past year)	−1.6%	(−2.1%, −1.0%)	13.3%	(11.7%, 15.0%)	8.6%	(7.3%, 10.1%)
Threaten someone with weapon (past year)	−1.8%	(−2.9%, −.7%)	3.8%	(3.0%, 4.9%)	2.6%	(2.0%, 3.6%)
Steal something worth <$50 (past year)	−2.3%	(−2.6%, −1.9%)	31.0%	(28.8%, 33.3%)	22.6%	(20.6%, 24.8%)
Steal something worth ≥$50 (past year)	−2.5%	(−3.2%, −1.9%)	10.6%	(9.2%, 12.2%)	7.6%	(6.4%, 9.0%)
Unstructured in-person socializing[b]						
Go out during the evenings for fun at least three times per week (vs. twice per week or less)	−1.8%	(−2.0%, −1.6%)	51.3%	(48.8%, 53.8%)	34.8%	(32.4%, 37.3%)
Go to parties at least once per month (vs. a few times per year or less)	−1.7%	(−1.8%, −1.5%)	73.6%	(71.5%, 75.7%)	52.2%	(49.7%, 54.7%)
Ride around in a car just for fun at least once per week (vs. twice per month or less)	−1.3%	(−1.4%, −1.1%)	64.3%	(62%, 66.6%)	55.0%	(52.6%, 57.4%)
Get together with friends informally "almost every day" (vs. at least once per week or less)	−2.3%	(−2.5%, −2.1%)	49.5%	(47.1%, 51.9%)	29.9%	(27.7%, 32.2%)

All trends statistically significant $p < .05$ except for cannabis.
CI = confidence interval.
[a] APC = "Annual Percent Change" (exponentiated coefficient of log-binomial model − 1) × 100. APC represents the relative change in the prevalence of a behavior each year (−5% indicates a 5% decline in the prevalence per year, i.e., relative risk of .95).
[b] Dichotomized at approximate 50th percentile of the distribution of the original ordinal variable.

Sample

Data from 12th-grade students for years 1999–2017 of MTF were combined into a data set containing a total of 44,842 observations. Year-specific sample sizes ranged from 2,096 to 2,579. Approximately 44% were under age 18 years, 49% were male, and 58% were white (nonweighted).

Missing data

Among all respondents, 1.5% did not answer any RB questions, .24% did not answer any UIS questions, and .22% did not answer any RB *or* UIS questions. Missing data for individual questions ranged from 2.1% to 6.3% for RBs and from .6% to 6.9% for UIS behaviors. Respondents missing on either all RB questions or all UIS questions tended to also be missing on demographic and sociodemographic variables (e.g., age, parent education). Among respondents who provided demographic data, males and "other" race were more likely to be missing on all RBs. The complete case method was used to estimate prevalence trends, and full-information maximum likelihood estimation was used in the structural equation modeling (SEM). Robust standard errors were used in both. Sensitivity test results are provided in the supplemental material (Appendix A).

Analyses

The four analysis steps are described in detail below. Analyses were conducted with Stata 14 (StataCorp LLC, College Station, TX) and MPlus version 8 (Muthén & Muthén, Los Angeles, CS) [24,25].

Step 1: prevalence trends. We estimated the survey-weighted prevalence of each binary RB and UIS behavior for each year (1999–2017). We then used log-binomial regression to determine the slope of change in the prevalence of each behavior during the years under study. Log-binomial regression is a generalized linear model that is well-suited for the present study aims because it yields risk ratio (RR) estimates (as opposed to odds ratio estimates produced by logistic regression) that directly correspond to the proportional change in prevalence for a given change in the independent variable. This allowed us to calculate the annual percent change (APC) in the prevalence of a behavior by including survey year (continuous variable) as a model predictor. Specifically, we calculated APC as (RR − 1) × 100. For example, an RR of .95 indicates a 5% decline (i.e., APC of −5%) in the prevalence per year. Supplemental figures are provided (Appendix B).

Step 2: factor analysis. We conducted two exploratory factor analyses using tetrachoric correlation and principal components extraction to determine whether (1) the nine dichotomous RB indicator variables (e.g., past 30-day cannabis use, past-year theft) formed a coherent latent RB factor and (2) the four dichotomous UIS indicator variables (e.g., spending time with friends) formed a coherent latent UIS factor. We considered a first unrotated principal component that explains ≥40% of total variability in the indicator variables as evidence of factor cohesiveness [26]. Lower values of R^2 (explained variance) would have suggested that a single latent factor would be insufficient to summarize between-person variation in the indicator variables. Supplemental analyses are provided (Appendices A and C).

Step 3: factor alignment. Declines in the prevalence of individual RBs (i.e., declines in "indicator" variables of a latent factor) stem from two sources: (1) declines in the mean of the latent factor and (2) measurement noninvariance of the factor indicator parameters (i.e., the *way* in which an indicator variable measures the latent factor is not stable over time). The first potential source—declines in the mean of the latent factor—is assumed to

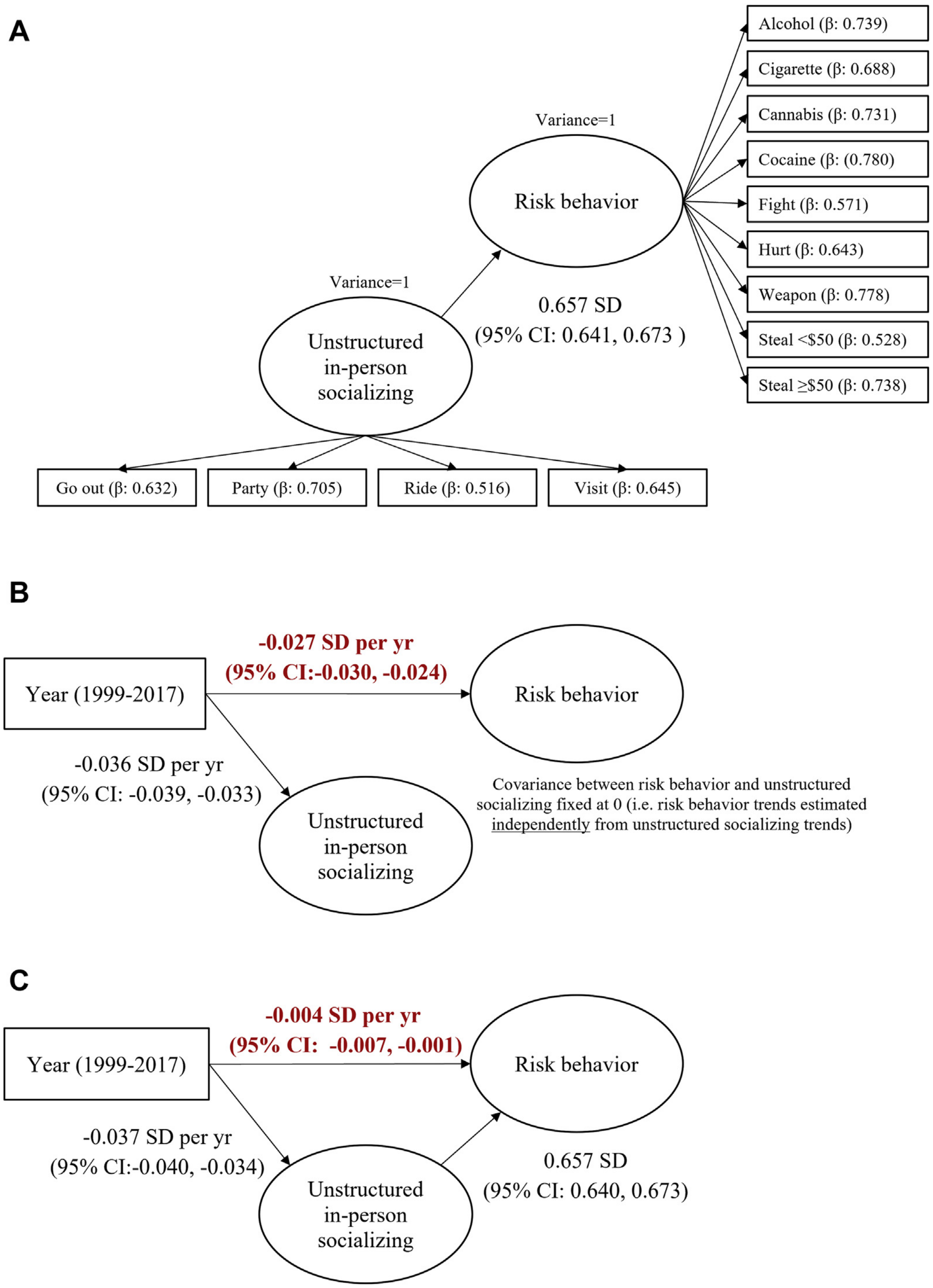

Figure 1. Sociodemographic-adjusted structural equation models examining the relationships among time (Years 1999–2017), risk behaviors, and unstructured in-person socializing for U.S. 12th graders (Monitoring the Future survey).[1]

reflect a decline in a general underlying tendency to engage in any type of RB.

Alternatively, the second potential source—measurement noninvariance—might reflect instances in which the prevalence of a specific behavior declines because of a specific environmental change that only affects that particular behavior. For example, tobacco policies have lowered the prevalence of youth cigarette use but presumably had little if any effect on the prevalence of youth cocaine use or youth fighting in school. In this case, the indicator variable for cigarette smoking would likely exhibit measurement noninvariance: declines in cigarette smoking might be observed even in the absence of overall declines in the postulated RB factor [15].

Our goal was to estimate declines in latent factor means (source one) while adjusting for measurement noninvariance (source 2). To accomplish this, we used the factor alignment method [25,27] to identify noninvariant indicators and incorporate the results into the structural equation models (described below). Factor alignment identifies measurement noninvariance by comparing factor indicator loading and threshold parameters within each group (e.g., each survey year) to those from a reference group (Year 1999). Additional details about factor alignment are available [27,28]. Supplemental results are available (Appendix D).

Step 4: SEM. Below, we describe the three parts (A, B, and C) of the SEM analysis. All analyses that examined the effect of survey year also included paths from year-specific dummy variables to specific measurement model indicator variables to correct for the measurement noninvariance identified in factor alignment results from Step 3 (described previously). For each of the three parts of the analyses below, we conducted sensitivity tests (1) using the complete case method (rather than full-information maximum likelihood) for missing data and (2) using a graded response model with the original, multicategory versions (rather than binary versions) of RBs and UIS behavior variables (Appendix A).

Part A (Figure 1A): To examine the relationship between RB and UIS, we created an unadjusted model with a path (i.e., regression) from the latent UIS factor (independent variable) to the latent RB factor (outcome variable). The adjusted model included sociodemographic covariates.

Part B (Figure 1B; Table 2 Models 1 and 2): We examined latent factor trends by creating an unadjusted model with a path from survey year (independent variable) to the RB factor (outcome variable) and another path from survey year to the UIS factor. The adjusted model included sociodemographic covariates. In both the unadjusted and adjusted models, we fixed the covariance between the RB and UIS factors to zero to estimate independent factor trends.

Part C (Figure 1C; Table 2 Model 3): Finally, we combined models from Parts A and B and estimated direct and indirect (i.e., via UIS) effects of survey year on the RB factor, using the UIS factor as a mediating variable.

Results

Prevalence trends of individual behaviors

The prevalence of most individual RBs and UIS behaviors declined by approximately 2% per year (i.e., a relative risk of approximately .98) (Table 1)—corresponding to an approximately 30% decline from 1999 to 2017 (Table 1). Notably, the prevalence of past 30-day cannabis use remained stable at approximately 24%. Figures of log-linear trends are provided in Supplemental Material.

Exploratory factor analysis

Consistent with prior studies [14,15], the RB factor explained 51.1% of the total variance in individual behaviors. RB factor loadings ranged from .67 to .79 (Appendix C). The UIS factor explained 56.7% of the variance in individual behaviors. UIS factor loadings ranged from .68 to .80 (Appendix C).

Factor alignment

Factor alignment analyses revealed a high degree of invariance (i.e., stability) among indicators. The observed noninvariance was concentrated among indicator thresholds for cannabis and cigarettes (consistent with prior results [15]). Approximately 5% and 1% of the parameters were noninvariant for the RB and UIS factor indicators, respectively (Appendix D). Both results fall below the 25% noninvariance guideline [27], which justifies factor trend analyses.

SEM Part A: association between RB and UIS factors

A model containing only the RB factor (outcome variable) regressed on the UIS factor (independent variable) yielded a standardized (i.e., range from −1 to 1) coefficient for UIS of .655 (95% CI: .639−.671)—indicating that a one standard deviation increase in UIS corresponded to a .655 standard deviation increase in RB, thus accounting for approximately 43% of the total variance in RB (Figure 1A). After adjusting for sociodemographic variables, the UIS coefficient changed minimally (β = .657, 95% CI: .641−.673; Figure 1A), and the model accounted for 45% of the variance in RB. When we subgrouped the data by each year, unadjusted coefficients for UIS ranged from .559 to .695 (median: .638).

SEM Part B: trends in RB and UIS factors

In an unadjusted model, the RB factor (outcome variable) mean declined by .026 (95% CI: −.029 to −.023) standard deviations per year (Table 2 Model 1)—corresponding to a decline of approximately .47 standard deviations from 1999 to 2017 (Figure 1B; Table 2 Models 1 and 2). The UIS factor (outcome variable) declined by .036 (95% CI: −.039 to −.033) standard deviations per year—a decline of approximately .65 standard deviations from 1999 to 2017. The sociodemographic-adjusted model (Figure 1B) yielded essentially the same results as the unadjusted model (Survey year β = −.027 and −.036 for RB and UIS, respectively). Importantly, almost all sociodemographic variables were statistically significant predictors of the RB factor. However, adjusting for sociodemographics had minimal impact on the coefficient for the survey year variable (compare survey year coefficient in Model 1 vs. Model 2 in Table 2), suggesting that these sociodemographics did not affect the *relationship* between survey year and RBs.

[1] Year-specific indicator variables were included in the three models above to adjust for the noninvariance identified in alignment model analyses. Sociodemographic covariates were also included in these three models. However, year-specific indicators and sociodemographics are not displayed because they are not central to model interpretation. All coviarances among year-specific indicator variables and between year-specific indicator variables and the all-years continuous variable are part of the above models. Note that more participants are retained in the full mediation model due to FIML and thus the effect estimates change slightly. Additionally, indicator variable loadings in Figure 1.1 will differ from loadings reported in the Exploratory Factor Analysis section of the manuscript due to different estimation methods used by MPLUS to create factor measurement model.

Table 2
Sociodemographic variables: relation to risk behaviors and statistical impact on the relationship between survey year (i.e., time) and risk behaviors

Independent variables	Dependent variable: Continuous latent risk behavior variable (lower values indicate less risk behavior)					
	Model 1		Model 2 (corresponds to Figure 1B)		Model 3 (corresponds to Figure 1C)	
	Beta	95% CI	Beta	95% CI	Beta	95% CI
Survey year	**−.026**	(−.029, −.023)[c]	**−.027**	(−.030, −.024)[c]	**−.004**	(−.007, −.001)[a]
Lives with father			−.162	(−.195, −.129)[c]	−.134	(−.166, −.102)[c]
Lives with mother			−.354	(−.400, −.308)[c]	−.281	(−.326, −.235)[c]
Father college educated			−.112	(−.144, −.08)[c]	−.072	(−.103, −.042)[c]
Mother college educated			−.010	(−.042, .022)	−.010	(−.040, .020)
Mother employed			.056	(.027, .085)[c]	−.034	(−.062, −.007)[a]
Number of siblings			.032	(.016, .047)[c]	.031	(.016, .046)[c]
Race (other vs. white)			−.142	(−.176, −.108)[c]	−.030	(−.062, .003)
Rurality versus urbanicity			.021	(.015, .028)[c]	.009	(.003, .015)[b]
Unstructured socializing					**.657**	(.640, .673)[c]

(1) Models are linear regression; (2) coefficients interpreted in terms of standard deviations of risk behavior (i.e., "the risk behavior factor decreased by .026 standard deviations per year"); (3) changes in the design of the MTF survey limit the ability to examine minority populations; (4) father employment status was not available; (5) robust standard errors and full information maximum likelihood applied; (6) [a]$p < .05$, [b]$p < .01$, [c]$p < .001$.
CI = confidence interval.

SEM Part C: mediation model

In the adjusted model, including the UIS factor as a mediator between survey year (independent variable) and the RB factor (outcome variable) reduced the magnitude of the direct effect for survey year from −.027 standard deviations per year to −.004 standard deviations per year (95% CI: −.007 to −.001) and yielded an indirect effect of −.024 (95% CI: −.026 to −.022; Figure 1C; Table 2 Model 3) (Figure 1C; Table 2 Model 3). Thus, UIS trends accounted for 85.7% of the *covariation* between survey year and the RB factor (i.e., 85.7% of the *decline* in RB from 1999 to 2017). In addition, the adjusted direct effect of UIS (independent variable) on RB (outcome variable) remained the same (β = .657, 95% CI: .640–.673), indicating that UIS continued to explain approximately 43% of the *overall* variability in RB. Complete case and graded response model sensitivity analyses yielded results essentially identical to the primary results (Appendix A).

Discussion

This study examined the relationship between national declines in RB and national declines in UIS among U.S. 12th graders from 1999 to 2017. We found a strong and consistent association

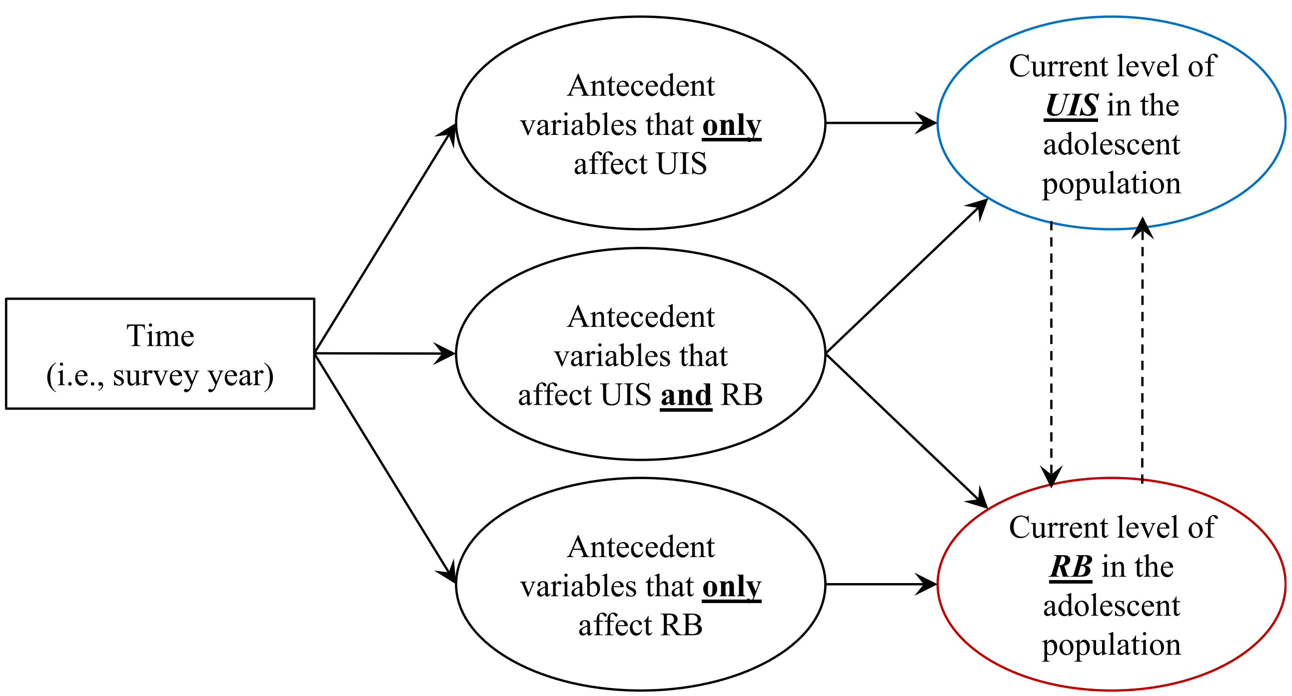

Figure 2. Conceptual model of possible causal relations underlying the observed association between adolescent trends in unstructured in-person socializing (UIS) and trends in risk behaviors (RBs).

between these two types of behavior. Moreover, we found a strong association between national declines in UIS and national declines in RBs. Although our analyses cannot establish a direct causal relationship between UIS and RB, we believe our results clarify important components of a larger network of relations that involve these constructs by highlighting that explanations for RB trends need to be able to account for UIS trends.

Below, we present a conceptual framework (Figure 2) to examine the role of unmeasured, causally antecedent variables (i.e., "upstream" causes) and the relative merits of different explanations for our results. For example, one potential explanatory pathway is Time → Changes in antecedent variables that only affect UIS → Declines in UIS → Declines in RB. However, another equally plausibly pathway is Time → Changes in antecedent variables that affect *both* UIS and RB → simultaneous declines in UIS and RB. Our results provide evidence that certain sociodemographic trends are less likely to be part of the list of possible antecedent variables, but additional work is still needed. For example, trends in antecedent variables such as parenting behaviors or participation in organized activities [29,30] may be driving declines in UIS and RB.

Importantly, there is also a path in which antecedent variables contribute to national declines in RB but are unrelated to national declines in UIS (Figure 2, bottom path). Our results demonstrate that national declines in UIS account for more than 80% of the declines in RB. This suggests that UIS and RB trends have *overlapping* antecedent causes, such as national changes in parental monitoring behaviors. Stated differently, our finding that UIS trends account for the majority of RB trends suggests that the "upstream" variables responsible for the declines in RB also played a large role in causing declines in UIS and vice-versa. Thus, any "upstream" causes that *only* affected RB without affecting UIS (e.g., tobacco control policies) may not be a significant contributor to population declines in RB. However, it is important to note that at the individual level, RB and UIS behaviors could affect each other directly via feedback effects (Figure 2, dashed arrows). For example, engaging in UIS may lead an adolescent to an enjoyable RB experience (e.g., alcohol use with peers) during one weekend, and that positive RB experience may increase the probability of engaging in UIS and RB the next weekend. The cumulative impact of these feedback effects is represented by the antecedent variable of the middle path in Figure 2. Stated differently, an adolescent's prior history of engaging in UIS and RB will impact that adolescent's survey responses at a particular point in time for both the UIS and RB survey questions.

We emphasize that this study examined cross-sectional, population-level shifts in behaviors, and thus, we cannot address the individual-level, within-subject developmental course of these behaviors. That is, we cannot establish whether engaging in behavior X at a time T affects the probability that *the same* individual will engage in behavior Y at time T+1. Although unstructured in-person peer socializing is believed to contribute to the emergence of RBs longitudinally [19,20,31], it is likely situated within a larger etiological network of individual-level characteristics (e.g., genetics) and environmental variables (e.g., socioeconomic status) that contribute to the development of RB for any particular adolescent.

As discussed earlier, unmeasured, causally antecedent variables that may be driving both national declines in UIS and RBs and will need to be evaluated in future studies. Here, we offer several potential candidates. First, parenting behaviors may be part of the explanation [32]. From 2002 to 2014, U.S. parents became more likely to check on their child's homework, provide positive affirmations, and strongly disapprove of substance use [29]. Parenting behaviors (e.g., oversight and communication) are known predictors of youth socializing and substance use behaviors [5,21,29]. Another phenomenon to consider is a rise in perfectionism. Youth seem to perceive greater societal demands and expectations of them and that meeting those expectations is a prerequisite for social approval [33]. These changes may have affected patterns of UIS and RBs. Finally, specific types of technologies may have a role. An analysis of 7,757 Swedish adolescents suggests that greater time allocated to highly immersive, competitive, and socially rewarding online games corresponds to less time spent socializing in-person with friends [34]. At present, approximately 80% of American adolescents have computer or video games at home, and close to one fourth play on a daily or near-daily basis for hours at a time [35].

Relatedly, there is speculation that new communication technologies (e.g., smartphones) have generated the observed declines by replacing in-person socializing [21,36]. However, youth who engage in the most electronic media communication seem to be the most likely to socialize in-person and use substances [16,37–39]. This pattern is consistent with studies from earlier eras. For example, when landline telephones were the dominant communication technology, youth who used substances also talked to friends on landline telephones more frequently and had more frequent face-to-face contact with those friends [40]. Given the similar behavioral dynamics across technologies, perhaps electronic media communication facilitates, rather than replaces, in-person socializing among some youth.

In addition, the prevalence of several behaviors postulated to mark adolescent maturation declined over the same period. Specifically, U.S. youth are not engaging in traditional "adult behaviors," such as having part-time employment, going on dates, and obtaining a driver's license [36]. A leading interpretation is that today's youth are taking a slower path to adulthood [36]. However, additional research is needed to clarify whether these trends are related to one another empirically—not theoretically—via examination of trends in individual-level behavioral covariation.

Additional limitations warrant comment. Although we examined a small number of sociodemographics, our analysis left many important variables unexamined (e.g., trauma, poverty, cultural differences, perceptions of risk and availability of substances, peer substance use, and deviance) [20,41,42]. In addition, the highest risk youth have high truancy rates, and thus, our analyses of this school-based survey likely exclude this group.

In sum, this study provides evidence that UIS behaviors (e.g., spending unsupervised time with friends) declined among U.S. 12th graders from 1999 to 2017 and that this decline is strongly associated with declines in RBs (e.g., substance use). It is unknown whether such effects are directly causal and/or influenced by unmeasured variables. However, the results provide evidence that national declines in UIS are a likely component of the explanation for national declines in adolescent RBs. To develop a complete understanding of changes in young people's behavior and well-being in the early 21st century, we encourage future research to examine the meaning of and reasons behind the declines in UIS and RBs among adolescents.

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Supplementary Data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.jadohealth.2020.12.144.

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