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Peer Network Processes in Adolescents' Health Lifestyles

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Abstract

Combining theories of health lifestyles—interrelated health behaviors arising from group-based identities—with those of network and behavior change, we investigated network characteristics of health lifestyles and the role of influence and selection processes underlying these characteristics. We examined these questions in two high schools using longitudinal, complete friendship network data from the National Longitudinal Study of Adolescent to Adult Health. Latent class analyses characterized each school's predominant health lifestyles using several health behavior domains. School-specific stochastic actor-based models evaluated the bidirectional relationship between friendship networks and health lifestyles. Predominant lifestyles remained stable within schools over time, even as individuals transitioned between lifestyles. Friends displayed greater similarity in health lifestyles than nonfriend dyads. Similarities resulted primarily from teens' selection of friends with similar lifestyles but also from teens influencing their peers' lifestyles. This study demonstrates the salience of health lifestyles for adolescent development and friendship networks.

Keywords

adolescents, health lifestyles, latent class analysis, social networks, stochastic actor-based models

Health lifestyles are defined as clusters of health behaviors that co-occur in patterned ways, undergirded by group-based identities and norms (Cockerham 2005; Mollborn, Domingue, and Boardman 2014). Health lifestyles offer a conceptual framework for understanding patterns of health behaviors, shedding light on persistent disparities in health behaviors, and explaining why such behaviors resist change. The health lifestyles that individuals adopt across the life course are influenced by social factors, with consequences for several important health outcomes (Burdette et al. 2017; Daw, Margolis, and Wright 2017; Lawrence, Mollborn, and Hummer 2017).

Health lifestyles theory emphasizes both the associations among various behaviors and the importance of social identities for the development of lifestyles (Cockerham 2005; Frohlich and Potvin 1999; Krueger, Bhaloo, and Rosenau 2009). Most notably for our purposes, Cockerham (2005) theorized the importance of peer effects among the social processes contributing to health lifestyle development, ranging from those based in social structure (e.g., socioeconomic status, demographics, etc.) to socialization and experiences (e.g., familial norms, formal education, etc.; Cockerham 2013). Peer effects represent an interesting blend of agency and structure because people both choose their peer groups and are influenced by them. However, despite early theoretical formulations anticipating peer effects in the construction,

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maintenance, and reproduction of health lifestyles, these effects have not been empirically tested.

We seek to assess whether health lifestyles display network effects consistent with theoretical expectations. "Network assortativity" describes a general pattern whereby friends exhibit elevated similarity on a range of attributes, including health behaviors, like physical activity (de la Haye et al. 2011) and substance use (Haas and Schaefer 2014; Kirke 2004), and core statuses that animate sociological research—gender (Kandel 1978), race (Moody 2001), and religious beliefs (adams, Schaefer, and Ettekal 2020). Beyond documenting the ubiquity of these *patterns*, network research can theoretically and empirically disentangle the causal *processes* responsible for observed assortativity (McPherson, Smith-Lovin, and Cook 2001). To identify these processes, models separate peer influence—people adopting the behaviors of their friends—from homophilous selection—choosing friends with similar behaviors (Steglich, Snijders, and Pearson 2010). Our primary research question therefore asks whether health lifestyles display network assortativity and if so, whether peer influence and homophilous selection processes underlie health lifestyle development.

We use data from two schools in the National Longitudinal Study of Adolescent to Adult Health (Add Health). We identify health lifestyles using latent class analysis (McCutcheon 1987; Vermut and Magidson 2002) that investigates combinations of 10 health behaviors. The analyses identify meaningful clusters of behaviors that differ across schools but are consistent over time within each school even as individuals change their own health lifestyles. Furthermore, these health lifestyles display assortativity: Health lifestyles are more similar among friends than other peers. We use stochastic actor-based models (Snijders 2011; Steglich et al. 2010) to assess peer influence and homophilous selection, finding that both processes contribute to observed assortativity among peers' health lifestyles. We decompose these results, finding that homophilous selection comprises the largest effect. We conclude that social networks and health lifestyles are intertwined.

BACKGROUND

Health Lifestyles

Health behaviors are not adopted in isolation. Adolescent health behaviors frequently co-occur (Brener and Collins 1998). Sometimes, co-occurring behaviors trend healthy or unhealthy. For example, adolescents who engage in risky sexual activity are also more likely to engage in substance use and fighting (Zweig, Phillips, and Lindberg 2002). Other times, co-occurring behaviors are a mix of healthy and unhealthy. For example, a large group of U.S. adolescents combine the most favorable exercise levels and dietary behaviors with the highest rate of binge drinking (Burdette et al. 2017). Research and prevention efforts can better explain adolescents' engagement in particular behaviors if they explicitly consider these complex interrelationships and their underlying influences and contexts.

Health lifestyles—interrelated health behaviors—are collective, reflecting group-based identities (Williams 1995). A particular clustering of behaviors reflects group membership (Sussman et al. 2007). For example, adolescents who consider themselves "jocks" and whose social circle consists of other "jocks" may engage in high levels of physical activity, unsafe habits, and binge drinking (Barber, Eccles, and Stone 2001). In other words, discordant combinations of healthy and unhealthy behaviors may be explained by an underlying group-based identity rather than by other characteristics such as personal commitment to maximizing healthy behavior (Stets and Burke 2000). Other group-based processes that shape behavior, such as norms, social learning, and role modeling, likely combine with—and are strengthened by—investment in a group-based identity. Together, these mechanisms of social influence can link group membership to a particular set of health behaviors.

Health Lifestyles in Adolescence

In adolescence, individuals initiate new health behaviors and increasingly make health behavior choices for themselves (Resnick et al. 1997). Multiple contexts are relevant for adolescent health behaviors, including families, neighborhoods, schools, and peers. Parents lay important foundations for the behaviors children adopt (Liefbroer and Elzinga 2012) dependent on social, economic, and demographic factors (Mollborn, Lawrence, et al. 2014). In schools and neighborhoods, peers, adults, and structural features establish norms that influence behavior (Gest et al. 2011).

Therefore, peers likely influence health lifestyles, particularly among adolescents. Peers act as referents, role models, and information sources who reinforce or sanction behaviors (Stead et al. 2011; Valente 2010). Such peer influences can have long-lasting consequences, partly due to ways that health behaviors cluster together (Mollborn, James-Hawkins, et al. 2014) and mutually reinforce each other (Ennett et al. 2006). Lifestyle patterns across contexts have not previously been investigated empirically, but because the groups underlying health lifestyles differ across settings, we expect that health lifestyles will be specific to those settings. Because health lifestyle theory links lifestyles to group identities, we expect lifestyles to be structurally consistent across time *within* contexts (assuming group identities within that context remain stable).[1] That is, even as individuals change their health behaviors over time, collective behavioral patterns should still reflect the lifestyle options available in that context. Therefore, the composition of lifestyles (i.e., structure) is recreated across time even as the individuals adopt a given lifestyle change.

We therefore expect to find meaningful clusters of health behaviors, including some that are consistently healthy or unhealthy and others that are discordant. We also expect the compositions of health lifestyles to vary across contexts, but within a context the composition of health lifestyles will be similar over time even as individuals change their behaviors and lifestyles.

Peer Network Processes and Health

Network research has consistently documented that people's social contacts include others who resemble themselves on a wide range of characteristics. This pattern is labeled *network assortativity* and is observed for numerous health behaviors and conditions (Schaefer and adams 2017; Valente 2010), including substance use (de la Haye et al. 2013; Haas and Schaefer 2014; Kirke 2004), physical activity (de la Haye et al. 2011), and psychological states such as depression (Schaefer, Kornienko, and Fox 2011). However, the vast majority of this research is conducted for single behaviors or conditions, with only one study examining multiple (religious) measures (adams et al. 2020). Thus, we first seek to identify whether health lifestyles display observed assortativity, as prior research has done for single behaviors.

Observed assortativity could result from several processes (Kandel 1978). Some assortativity is expected by chance alone due to the unequal distribution of characteristics in a population (Blau 1977; Marsden 1988), but two primary processes operate above and beyond this baseline: peer influence and homophilous selection.

Assortativity arises from *peer influence* when individuals adopt the behaviors or attitudes of their friends (Snijders 2011; Steglich et al. 2010). Peer influence is supported by sociological and psychological theories, including social learning from one's peers, normative influence, behavioral modeling, a need for belonging, and others (Brechwald and Prinstein 2011; Friedkin and Cook 1990). Peer influence assumes that if person i names person j as a friend at Time 1 but they differ on a (changeable) attribute, i will have an increased probability of changing their behavior to match j's at Time 2 (see Column I of Figure 1). Although theoretically appealing and frequently evoked to explain network similarity (Smith and Christakis 2008), influence is notoriously hard to identify empirically (Cohen-Cole and Fletcher 2008) and difficult to disentangle from homophilous selection (Shalizi and Thomas 2011).

In contrast to peer influence, *homophilous selection* produces network assortativity when people are more likely to form new relationships with peers with whom they share characteristics (Kandel 1978). Although network scholarship typically describes homophilous selection as a singular process, it is composed of two phenomena: the creation and dissolution of friendships (McPherson et al. 2001). The creation of friendships is depicted in Figure 1 (top row of homophilous selection). According to homophilous selection, if person k and person l share an attribute (e.g., a health lifestyle) but are not friends at Time 1, there is an increased likelihood of k and l becoming friends by Time 2. Dissolution (bottom row of homophilous selection) represents the converse of this process. If persons m and n are friends at Time 1 but differ on an attribute like health lifestyles, homophilous selection would expect a higher likelihood of their friendship dissolving (for further elaboration, see Snijders 2011).

Summary

Our overarching question is whether health lifestyles serve as a basis for homophilous selection and peer influence processes within adolescent social networks. To answer this question, we assessed whether health behaviors clustered together in empirically identifiable profiles of behaviors (i.e., "health lifestyles") within schools, evaluated if health lifestyles were more similar among friends than other peers (i.e., assortativity on health lifestyles), and examined the extent to

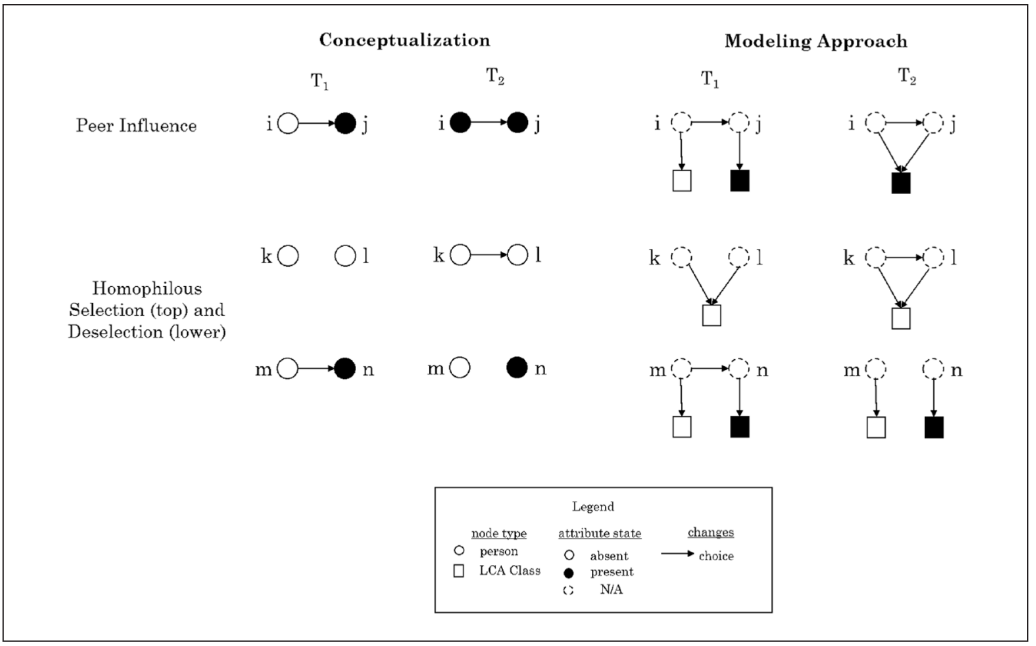

Figure 1. Conceptualizing and Modeling Peer Influence and Homophilous Selection.

which peer influence and homophilous selection processes contributed to this similarity.

DATA AND METHODS

We used data from the two largest saturated schools in Add Health (Bearman, Jones, and Udry 1997).[2] These schools (frequently referred to by the pseudonyms Jefferson and Sunshine High Schools) represent distinct social contexts and are common for benchmarking social network change estimation (Green et al. 2013; Haas and Schaefer 2014). Jefferson was a mostly white Midwestern school, and Sunshine was a much larger, ethnically diverse Western school. Our data came from two in-home interview surveys approximately 1 year apart: Waves I and II.

Our analyses proceeded in two primary steps that separately estimated health lifestyles and then modeled network dynamics using those health lifestyles. Given that we conceptualized health lifestyles as a context-specific phenomenon, we fit latent class analysis (LCA) models using all adolescents with available data in each school irrespective of their inclusion in subsequent models.[3] The stochastic actor-based models (SABMs) included only those in the network data. The SABM sample was marginally younger at Wave I than the full sample (by design) but otherwise comparable.

Identifying Health Lifestyles with LCA

We used LCA (McCutcheon 1987; Vermut and Magidson 2002) to estimate health lifestyles from a comprehensive set of health behaviors. Following theoretical development and previous empirical work, we selected 10 health indicators representing the range of behavioral domains previously identified as useful for defining adolescents' health lifestyles (Burdette et al. 2017; Cockerham 2005; Daw et al. 2017; Lawrence et al. 2017; Mollborn, Domingue, and Boardman 2014).[4]

The first domain, substance abuse, was represented by four indicators. Smoking was coded as nonsmoking, infrequent (1–11 days per month), and frequent smoking (≥12 days). Drinking was coded as nondrinking (0), moderate (1), and heavy, binge, or problem drinking (2) in the past year. Heavy drinking was more than 8 drinks per week for women or more than 15 for men, binge drinking entailed drinking 5 or more drinks in a row, and problem drinking identified social or physical problems resulting from alcohol consumption. Variables for other (chewing) tobacco and drug use were each coded as 1 if adolescents had used them within the past 30 days and 0 if they had not.

The second domain was activity level. One indicator summed how many times the respondent had engaged in different physical activities (bicycling, softball, etc.) during the past week, recoded into light (0–3), moderate (4–6), and heavy activity (7–15). The second indicator measured hours per week spent watching television or videos and playing video games, recoded into low (2 hours/day or less), moderate (>2 and ≤4 hours), and high (>4 hours).

The final four domains were represented by single indicators. Sexual activity measured the respondent's most recent sexual encounter with categories for no sex, sex with a condom, and sex without a condom. Safety captured respondents' seatbelt use, coded as 1 for always and 0 for others. The health care domain was represented by whether the respondent had received a checkup with a doctor and dentist within the past year, coded as 1 for those who had visited both and 0 for those who had not. Finally, sleep was coded as 1 for those who indicated that they received enough sleep and 0 for those who did not.

We fit separate LCA models for each school at each wave, using *poLCA* in R (Linzer and Lewis 2011), generating four sets of class assignments. LCA uses maximum likelihood to identify a categorical latent trait that underlies observed associations among indicators. The categorical latent variable is defined by the patterns of conditional probabilities among items, which are assumed to be conditionally independent given the categorical latent trait. In contrast to an index or regression-based approach that identifies individual associations with an outcome, LCA allows complex patterns to emerge from the data.

For each LCA model, we examined solutions for 2 to 12 classes and selected the best for use in network analysis—based on substantive interpretation and fit statistics, including the Bayesian information criterion (BIC), Akaike information criterion, and G^2 (Linzer and Lewis 2011; Vermut and Magidson 2002).[5] We used the "classify–analyze" approach that separated the modeling into two steps (Bray, Lanza, and Xianming 2015), assigning individuals to the latent class with the largest posterior probability (i.e., classify) and then estimating network models using this nominal variable (i.e., analyze). We employed this approach for two reasons. First, no modeling approach combines estimating latent classes with network dynamics into a single framework, allowing for estimating selection and influence in a manner akin to SABM. Second, our approach was a conservative test because associations are expected to be biased downward (Bolck, Croon, and Hagenaars 2004). Average class assignment probabilities exceeded .80 (range = .81–.86), suggesting minimal misclassification bias (Jung and Wickrama 2008).

Modeling Network Dynamics with SABMs

We used these latent class assignments, or health lifestyles, to model friendship and health lifestyle coevolution. The state-of-the-art approach to modeling such network dynamics is SABMs (Snijders 2001; Steglich et al. 2010). SABMs permit the simultaneous estimation of changes in friendships and class membership while allowing endogenous effects between the two. Thus, we tested how the evolving network structure affected health lifestyle class membership (peer influence) alongside the effects of health lifestyle on adolescents' choices of friends (homophilous selection), net of standard controls.

The SABM aimed to recreate the network and class membership changes observed at Wave II. This was accomplished by specifying an objective function for each outcome (i.e., friendship network and lifestyle class). These two objective functions contained effects representing the mechanisms that drive change in network and lifestyle outcomes. The model assumed that individuals made changes to their outgoing network ties and behavior to maximize these objective functions. SABM estimation uses an agent-based model to obtain parameter estimates, reflecting each effect's relative strength.

The network objective function estimated individuals' likelihood of forming or maintaining ties relative to failing to form or dissolve ties, respectively. We focused on whether friendships are more likely among individuals with the same health lifestyle class (homophilous selection). This process is illustrated in Figure 1, where adolescents k and l belonged to the same LCA class and became friends over time, whereas m and n, who were members of different classes, dissolved their friendship. We represented this form of selection using the effect for same class membership, which measured whether the adolescents in each dyad were the same or different (Ripley et al. 2019). A positive parameter estimate for this effect indicates that dyads belonging to the same class were more likely to exhibit friendship over time (either by forming a tie or maintaining an existing tie).

The SABM behavior objective function predicts changes in individuals' behavior as a product of their own attributes, others' attributes (i.e., influence), and network structural features. SABMs have most often been used to model change in a single dichotomous or ordinal behavioral variable (Steglich et al. 2010); however, they can accommodate latent classes (adams et al. 2020), such as our categorical health lifestyles. To accomplish this, we adopted the strategy for modeling "behavioral" variables within an SABM as a two-mode network (Snijders, Lomi, and Torló 2013), coding each adolescent as having a membership state for each of the classes (or categories of affiliation), with 1 coded for the assigned class and 0 coded for the other classes. There were two time points of these two-mode networks, representing LCA class membership for each school. Peer influence was modeled using the "to" effect in the behavior function, and homophilous selection was modeled using the "from" effect in the network function (Ripley et al. 2019). The difference between this modeling strategy and the conceptualization of selection is represented in Column II of Figure 1, where *i* and *j* are friends at Time 1 but have different lifestyle class memberships—where class is denoted as a membership (square) rather than a nodal attribute. We were primarily interested in whether adolescents adopted the same lifestyle class as their friends, expecting that adolescents chose the most common class among their friends. We tested this with an effect representing how many of each adolescent's current friends belonged to each class. A positive parameter estimate indicated that adolescents were more likely to choose a lifestyle class when they had more friends in the class. Given the evolving nature of the network and lifestyle classes, friends' lifestyles also changed endogenously.

The SABM assumes that changes in the network and behavior between the two observed waves of data occur in continuous time through a sequence of microsteps (adams and Schaefer 2018; Ripley et al. 2019) and that during a given microstep, one actor can make one change to either the network or LCA class (i.e., change follows a Markov process). Rate functions corresponding to each network and behavior function indicate how many opportunities actors are given to make changes. We specified each rate function to be uniform across actors. We constrained the model such that adolescents could not have more than 10 outgoing ties (to be consistent with the Add Health data collection design) or two class memberships. This latter requirement was needed because the Markov assumption behind the SABM allows for only one change per microstep. Thus, individuals could not simply switch from one class to another because this would represent both the dissolution of a tie to one class and the creation of a tie to another class. By allowing up to two LCA–class memberships, adolescents in a given class could switch from their current class to another by either adding a tie to the new class (keeping their current membership until a later microstep) or dropping their current membership and adding the new membership in a later microstep. Negative outdegree effects served as a deterrent to belonging to multiple classes.

Following SABM best practices, our models included additional controls. Standard individual-level controls were included in both the network and behavior functions for gender (male as reference category), age (in years at Wave I), race-ethnicity (for Sunshine only; non-Hispanic white as reference), GPA (4-point scale), and parents' highest level of completed education. We allowed each of these attributes to have a separate effect on each class. To specify this in the SABM, we set the healthy class as the reference and included interactions between dummy variables representing each other class and sociodemographic measure. Hence, main effects of attributes represented the effects of demographic (and other) variables on the likelihood of selecting the healthy class, whereas the interactions represented how the effect of the attribute on the likelihood of selecting the respective class departs from its effect on selecting the healthy class. As noted previously, the behavior function included an actor outdegree effect that represented the likelihood of observing any tie in the two-mode network (i.e., having a health lifestyle class). To allow class membership rates to differ, we treated the healthy class as the reference category and added interactions between dummy variables for the other classes and actor outdegree.

The network function included controls that captured the possibility that the attribute affected individuals' likelihood of being selected as a friend (i.e., attribute-based popularity), which, for parsimony, was dropped from the model if not significant (Ripley et al. 2019). The network function also included controls for other normative friendship processes, including homophilous selection on other attributes (race-ethnicity, gender, academic achievement, and socioeconomic status) and endogenous network effects (e.g., reciprocity, which is the increased likelihood of *i* nominating *j* as a friend given *j*'s nomination of *i*). The network function also included controls for structural opportunities for friendship with effects representing, for each dyad, whether or not they were in the same extracurricular activity (Schaefer et al. 2011) or were coursemates (weighted; Frank et al. 2008).

Additional controls addressed alternative mechanisms. For instance, friendships developed in contexts like extracurricular activities or classrooms probably exhibit assortativity on attributes associated with membership in the context (e.g., friends are likely to be similar in physical activity when their friendship developed within a sport context). Assortativity can also arise when a friendship emerges between two individuals because of a common friend (i.e., transitivity, the increased likelihood of a friendship between pairs of people who share other friends in common). Transitivity amplifies levels of assortativity if the common friend shares a common attribute with the two friends, in which case the process of transitivity can create network assortativity even in the absence of homophilous selection (Moody 2001; Wimmer and Lewis 2010). Indegree-popularity accounts for one's general tendency to receive tie nominations given how many ties one has already received, outdegree-popularity represents one's tendency to receive ties given how many ties one has sent, and indegree-activity is one's general tendency to send ties given how many ties one has received (Ripley et al. 2019). By specifying these effects, our SABM was able to differentiate which among the various selection mechanisms was responsible for the observed network patterns.

Last we used a decomposition approach (Steglich et al. 2010) to ascertain the relative importance of peer influence versus homophilous selection in producing observed health lifestyle assortativity. This multistep procedure used the agent-based model core of the SABM to simulate network–lifestyle co-evolution based on estimated model parameters. We compared the simulated levels of assortativity for the full estimated model with levels observed in a series of simulations that systematically constrained individual key effects to zero (i.e., peer influence, homophilous selection). The magnitude of the decrease in assortativity when an effect was constrained to zero indicated the mechanism's relative contribution to observed assortativity. This procedure was repeated for each set of processes labeled in Figure 4. We measured lifestyle assortativity using α (Moody 2001) and averaged results across 1,000 simulations per specification for each school.

We estimated the SABMs separately by school given that they represent independent contexts with no possibility of ties between schools. High school seniors at Wave I were excluded from analysis because they were not observed at Wave II. We estimated SABMs with RSiena (Version 1.1–232; Ripley et al. 2019) using standard RSiena settings to impute data for anyone else missing from Wave II (i.e., those lost through attrition) and for other forms of missing data (Huisman and Steglich 2008). We conducted postestimation checks to ensure adequate model convergence and goodness of fit (Lospino 2012); see Figures A1 and A2 in the online version of the article.

RESULTS

Table 1 provides descriptive statistics for students in Jefferson and Sunshine High Schools by wave. Because Sunshine included only Grades 10 through 12, its attendees were older than Jefferson's. As previously shown (Moody 2001), these schools' racial-ethnic composition differed substantially. The prevalence of several behaviors was similar across schools, whereas others differed. For example, similar proportions of students in each school reported engaging in no sexual activity and condom use at last sex among the sexually active. In contrast, Jefferson students had lower average screen time but higher rates of substance use (smoking, drinking, and other tobacco use) than Sunshine students.

Health Lifestyles

We estimated one latent class model for each school for each wave. For each model, we selected the three-class solution as the best fitting. For three of the four models (Jefferson at both Waves I and II, Sunshine at Wave I), the adjusted BIC (see Table A1 in the online version of the article) indicated that a three-class solution best fits the data. Moreover, within each solution, the classes had interpretable distributions of variables across the indicated classes. For Sunshine at Wave II, the adjusted BIC suggested that the best fitting solution had two classes, but we chose the three-class solution because it showed a trivial statistical fit difference compared to the two-class solution, it was compositionally comparable to the three-class solution for the other models, and a consistent solution set allowed us to address our aims of examining network selection and influence processes more parsimoniously.[6]

Figure 2 displays results from the three-class solutions for each school by wave. These radar plots correspond to transformations of the class-conditional response probabilities (ρ) that can be interpreted as the probability of class members being in the top-coded category for each health behavior (adams and Lippert 2019). The plots present items normalized within a 0 to 1 range and standardized in a consistent (healthy) direction.[7] For the standardization procedure and the full set of class-conditional response probabilities, see Table A2 in the online version of the article.

Table 1. Respondent Descriptive Statistics, by School and Wave, with Data from the National Longitudinal Study of Adolescent to Adult Health Waves I and II.

	Jefferson High School		Sunshine High School	
	Wave I	Wave II	Wave I	Wave II
Sociodemographic characteristics				
Age				
14–15	.27	.06	.10	.01
16–17	.49	.59	.62	.55
18–19	.23	.35	.28	.44
Female	.47	.48	.48	.50
Race-ethnicity				
White	.97	.98	.05	.05
Black	.00	.00	.23	.22
Hispanic	.01	.01	.39	.41
Asian/Pacific Islander	.00	.00	.31	.30
Other	.01	.01	.01	.02
GPA	2.62	2.58	2.51	2.62
Parental education				
< High school	.03	.03	.22	.22
High school grad	.39	.39	.22	.21
Some college	.25	.25	.22	.21
Four-year degree	.34	.33	.35	.36
Health behaviors				
Smoking				
None	.51	.44	.78	.73
Infrequent	.16	.18	.13	.16
Frequent	.32	.39	.09	.11
Drinking				
None	.33	.36	.50	.57
Moderate	.14	.08	.11	.08
Heavy/problem	.53	.56	.39	.35
Other (chewing) tobacco use	.15	.16	.03	.04
Drug use	.28	.27	.21	.21
Physical activity				
Heavy	.36	.29	.30	.24
Moderate	.29	.33	.33	.32
Light	.35	.38	.37	.44
Screen time				
Low	.55	.61	.42	.43
Moderate	.26	.21	.30	.30
High	.19	.18	.28	.27
Sexual activity				
None	.52	.52	.51	.54
Condom at last sex	.28	.31	.26	.26
No condom at last sex	.20	.17	.23	.20
Health care use	.52	.53	.39	.35
Sufficient sleep	.69	.71	.64	.62
Regular seatbelt use	.55	.57	.68	.67
N	832	635	1,719	1,199

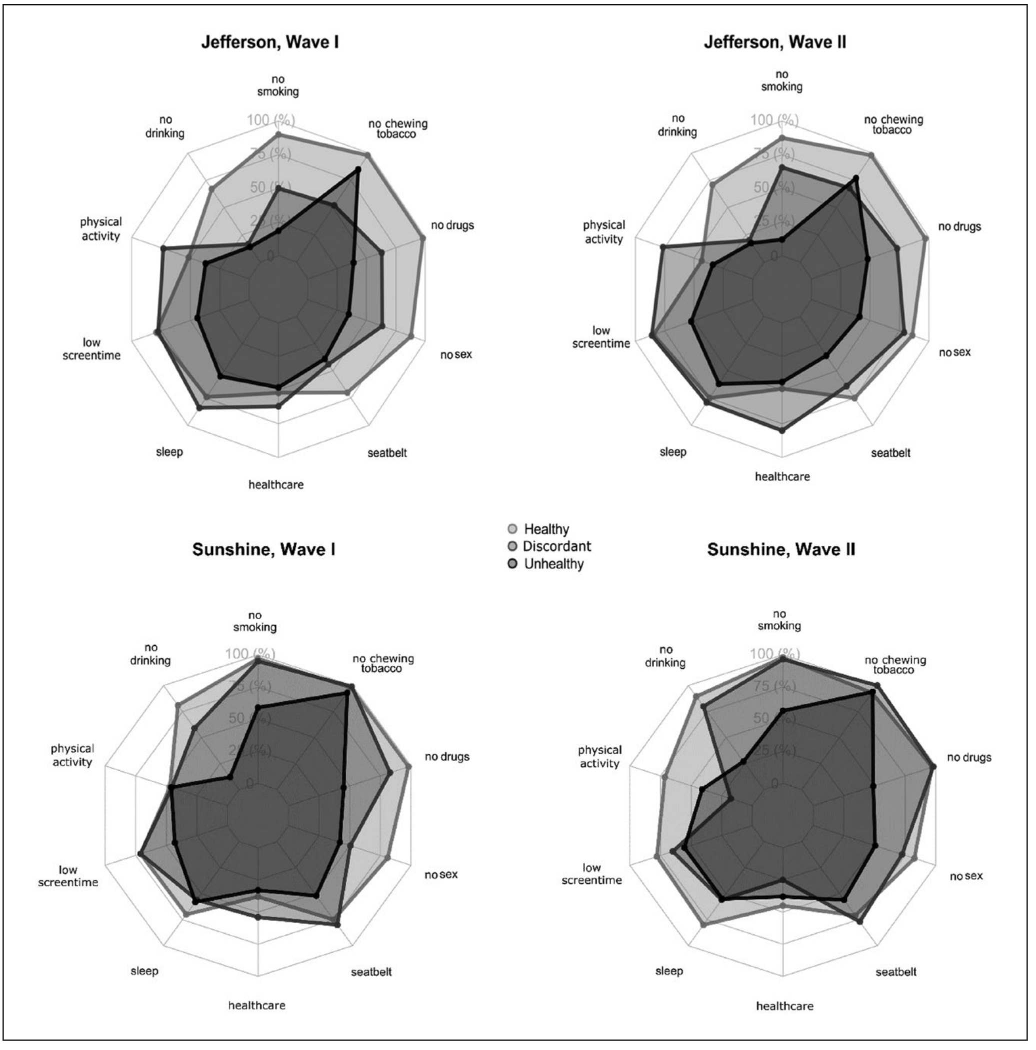

Figure 2. Class-Conditional Response Probabilities from Latent Class Analysis, by School and Wave, with Data from the National Longitudinal Study of Adolescent to Adult Health Waves I and II.

Note: The categorical response probabilities were rescaled to a uniform scale from 0 to 1, with 0 representing the lowest possible value and 1 the highest for each variable (see details in Table A2 in the online version of the article). For trichotomous variables, this required multiplying the category-specific response probabilities by a scaling factor (0 for lowest category, .5 for moderate, and 1 for the highest). These then essentially reflect the class-conditional likelihood of selecting the highest category for each variable. For the sexual activity variable, the ordering is no sexual activity, condom at last sex, no condom at last sex.

Figure 2 conveys several key points. First, the health lifestyles reflect concordant and discordant groups that differ somewhat by school. We summarize the three classes identified in each school at both waves with the labels *mostly healthy*, *mostly unhealthy*, and *discordant*. Although we rely on these shorthand labels, patterns are more complex. Members of the mostly healthy class also typically exhibited some unhealthy behaviors, those in the unhealthy classes reported some healthier behaviors, and the discordant groups reflected combinations of healthy and unhealthy patterns. For example, members of the Wave I Jefferson discordant class were substantially more likely to use chewing tobacco than the unhealthy class.[8] Consistent with our expectations, the complex patterns of behaviors within each latent class provide empirical support for the health lifestyles approach within these two schools (e.g., as opposed to an index).

In each model, the healthy group had high rates of nonsmokers, nondrinkers, those who have not had sex, and those who always wore a seatbelt. The unhealthy groups all showed high rates of drug/alcohol/smoking use, not using a condom during last sex, and lower levels of physical activity. However, the patterns in the discordant groups diverged between the two schools. Those in the discordant group at Jefferson showed high rates of physical activity, getting enough sleep, and visiting the doctor and dentist but also substantial substance use, including smoking, drinking, tobacco chewing, and drug use. In contrast, those in the discordant group at Sunshine had fairly low rates of substance use but also low rates of physical activity, getting enough sleep, and use of health care. In sum, those in the discordant class at Jefferson were slightly more likely to actively engage in behaviors (whether healthy or not), whereas those in the discordant class at Sunshine were more passive (avoiding behaviors, whether healthy or unhealthy). These divergent patterns suggest that prevalent adolescent health lifestyles varied by school context.[9]

Health lifestyle patterns over time differed by school. In Jefferson, the prevalence of each health lifestyle remained similar over time, with a slight decrease in the percentage in the healthy class (49% to 41%) corresponding to an increase in the unhealthy class (33% to 40%), whereas the discordant class remained stable (19%). Sunshine displayed greater shifts in prevalence, with the healthy group dropping from 53% to 26%, corresponding with increases in the mixed class (15% to 35%) and a slight increase in the unhealthy class (32% to 39%). Surprisingly, even more students changed their health lifestyles than these compositional shifts might suggest: About 47% of Jefferson students and 66% of students in Sunshine changed their health lifestyles from Wave I to Wave II.

Although many students changed health lifestyle, the school-level prevalence of each health behavior displayed remarkable sample-level stability across waves. For example, rates of getting enough sleep were 69% in Wave I and 71% in Wave II for Jefferson and 64% and 62% in Sunshine. The similar prevalence in Waves I and II obscures the changes: 25% of Jefferson students and 29% of Sunshine students changed their sleep status (either from enough to not enough or from not enough to enough) between the waves. These behavioral and lifestyle changes are consistent with prior literature on adolescence (Daw et al. 2017).[10]

Importantly, the contextual composition of classes remained relatively robust to these underlying individual changes. That is, the composition of health lifestyle classes appears to have been consistent over time within contexts—with the noted exception of Sunshine's discordant class. This class remained "passive" by not engaging in behaviors that were either health promoting or compromising but became more passive across waves (e.g., decreasing in both drinking and physical activity). Because we separately fit models for each school at each wave, this is a novel, empirically observed contextual consistency in class compositions, not an artifact of modeling.

Networks

Table 2 describes the schools' friendship networks, each of which exhibited distinct network characteristics. The out-degree values indicate the proportion of friends in a school, and the lower values for Sunshine demonstrate that Sunshine students reported substantially fewer within-school friends than their Jefferson counterparts.[11] Consistent with prior research, Jefferson students had a higher proportion of their friends within the school, whereas Sunshine provided a more porous boundary for adolescents' reported friendships (Moody 2001). The Jaccard indices (.34 for Jefferson, .21 for Sunshine) indicate that each school had sufficient stability in the observed friendship networks to justify our SABM approach.[12]

Table 2 also provides evidence that health lifestyles displayed strong network assortativity in each school: Friends were more likely to share a health lifestyle. The LCA class assortativity, or α segregation index, measures observed health lifestyle assortativity in each school (Moody 2001).[13] The odds ratios indicate that in each school, at both waves, the odds of a friendship between adolescents in the same LCA class were significantly greater than adolescents with different classes. For example, at Wave I, the odds of a same-class tie were 85% greater in Jefferson and 62% more likely in Sunshine compared to ties between adolescents from different classes. We used the SABMs to explain this strong health lifestyle assortativity.

Network Processes for Health Lifestyles

We estimated separate SABMs for each school to test homophilous selection and influence processes while controlling for standard potentially confounding factors. For brevity, we focus our discussion on

Table 2. Network Descriptive Statistics, by School and Wave, with Data from the National Longitudinal Study of Adolescent to Adult Health Waves I and II.

	Jefferson High School		Sunshine High School	
	Wave I	Wave II	Wave I	Wave II
Out-degree (mean)	4.15	3.05	2.02	1.38
LCA-class assortativity (α)[a]	1.85	1.91	1.62	1.51
Jaccard index[b]	.34		.21	

Note: LCA = latent class analysis.
[a]LCA class-based assortativity is estimated using Moody's (2001) α segregation index. The observed αs indicate the odds of a tie existing that includes two adolescents with the same LCA class relative to the odds of a tie between two adolescents with different LCA classes. All α values are significant at $p < .05$.
[b]The Jaccard index indicates the amount of stability observed between the two waves of network observations. Snijders et al. (2010) recommend that estimating stochastic actor-based models require values greater than .20.

the health lifestyle–related effects shown in Figure 3 that correspond to our focal questions. Although we present these estimates within a single figure, we caution readers to not directly compare effect sizes in Figure 3 because the scales and control terms are specific to each model and not comparable. For full model specifications, see Table A3 in the online version of the article; controls operated consistently with prior studies.

In the behavior function, our key process of interest was peer influence, represented by the *friend with same LCA class* effect. In both schools, this effect was statistically significant (i.e., different from zero, $p < .001$) and positive, indicating that adolescents were more likely to adopt a lifestyle class as their number of friends in that class increased. In Jefferson, the influence estimate of .43 indicates that for each additional friend an adolescent had in a particular lifestyle class, the odds of choosing that class increased by 53% (exp[.43]), all else being equal. For Sunshine, the estimate reflects a 30% increase (exp[.26]) in selecting a class for each additional friend the adolescent had with that class. These effects offer evidence of peer influence on health lifestyles in both schools.

Turning to the network function, homophilous selection is represented by the *LCA (same category)* effect. In both schools, this effect was positive and statistically significant. These coefficients can be interpreted as the difference in the likelihood of a friendship being formed or maintained for two adolescents with the same lifestyle class (coded 1) versus two adolescents from different classes (coded 0). Thus, for Jefferson, the odds of a tie between adolescents with the same class were 2.7 (exp[1.01]) times the odds of a tie between dissimilar adolescents, all else being equal. Sunshine, although demonstrating a large and significant selection effect, also showed a wide confidence interval around this estimate.

To compare across models and parameters, our final step decomposed the relative contributions of homophilous selection and peer influence to health lifestyle assortativity; see Figure 4. In both schools, homophilous selection carried the greatest weight in producing lifestyle assortativity, responsible for 68% and 55% of assortativity in Sunshine and Jefferson, respectively. In contrast, peer influence was responsible for only 11% and 20% of assortativity, respectively. The proportions for trend indicate that 5% and 10% of assortativity change was due simply to rates of change in network and individual class memberships. Controls accounted for only 2% to 3% of changes in lifestyle assortativity. Finally, 12% to 13% of assortativity could not be precisely allocated to any of these (Steglich et al. 2010). In sum, the observed assortativity on health lifestyles in Jefferson and Sunshine High Schools appears to have been primarily the result of homophilous selection, albeit also exhibiting significant peer influence. These results offer strong and consistent support for our approach in identifying network processes underlying health lifestyle–based behavioral clusters.

DISCUSSION

Our aim was to explain if and how network processes are related to adolescent health lifestyle development. We found that adolescent health lifestyles were specific to context but structurally similar over time because the lifestyle compositions differed across the two schools but were mostly consistent within schools over time. These health

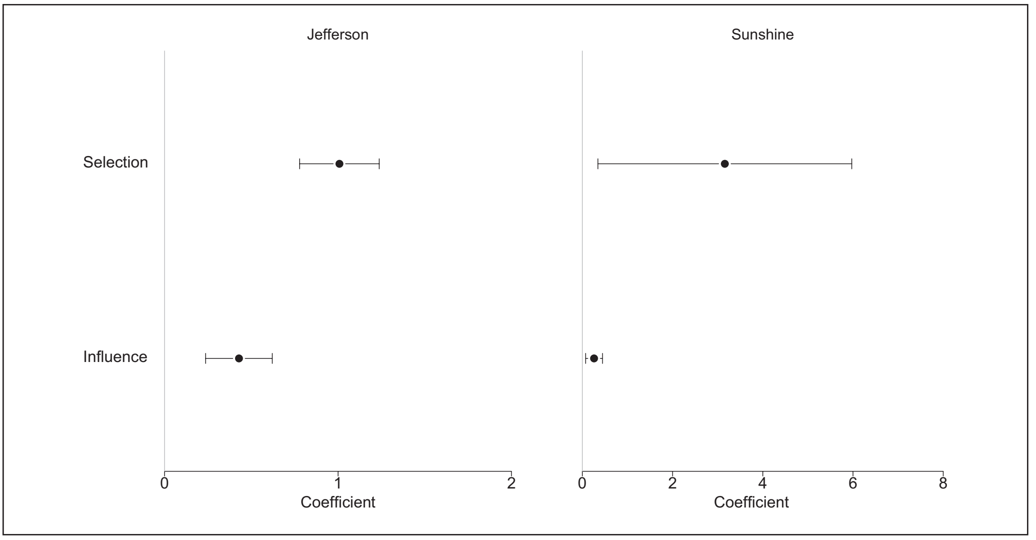

Figure 3. Peer Influence and Homophilous Selection of Health Lifestyles from Stochastic Actor-Based Models, by School, with Data from the National Longitudinal Study of Adolescent to Adult Health Waves I and II.
Note: Behavior function (influence effect) controls for age, gender, GPA, race (Sunshine only), and parental education. Network (selection effect) function controls for density; reciprocity; transitivity; (square root) in-degree; number of shared courses and extracurriculars; ego/alter/similarity: gender, grade, race (Sunshine only), and parental education, and GPA.

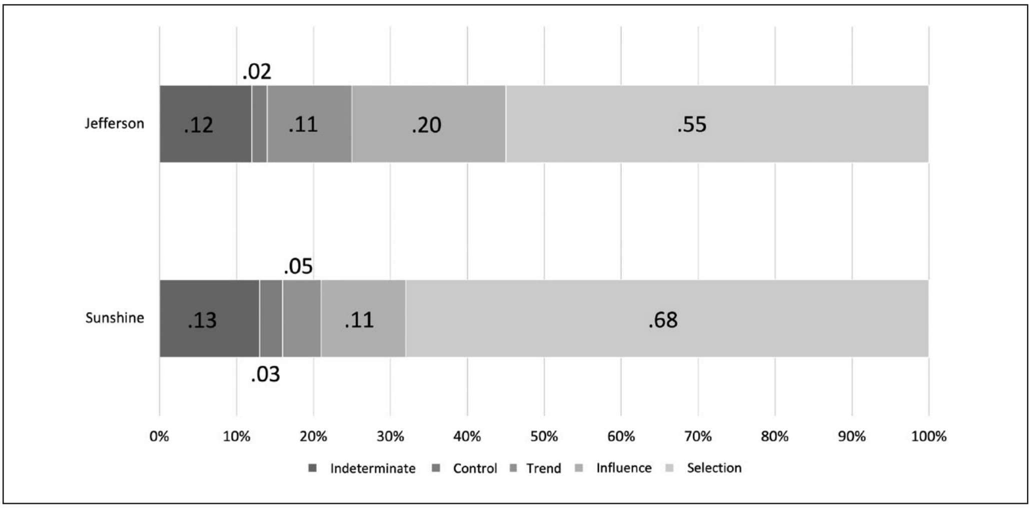

Figure 4. Health Lifestyle Assortativity Decomposition, by School, with Data from the National Longitudinal Study of Adolescent to Adult Health Waves I and II.
Note: This decomposition accounts for how much of the observed changes in health lifestyle assortativity can be attributed to four separate processes. (Right to left): Homophilous selection and peer influence are the key processes of interest in the article; the trend accounts for baseline changes in the network and latent class analysis class membership, whereas control accounts for changes deriving from other factors included in the model. These four leave some proportion of the observed changes unaccounted for in the model (indeterminate).

lifestyles displayed strong network assortativity, which was the result of both peer influence and homophilous selection processes, although the latter was stronger. We connect these results to prior research and draw out their implications in the following.

Health Lifestyles

Our LCA-identified health lifestyles showed similar patterns to previous research using Add Health data (Burdette et al. 2017; Daw et al. 2017; Lawrence et al. 2017). The nature and composition of our discordant classes were somewhat similar to Burdette et al.'s (2017) larger Add Health sample. Teen respondents' relatively high rates of change in their health lifestyles from one year to the next is also consistent with trajectories of lifestyle development over the life course (Daw et al. 2017; Frech 2012). Our study is the first to model health lifestyle classes within local settings. We theorized that lifestyles would vary across schools, and our results bear this out. Further research across a broader range of contexts will likely shed light on contextual determinants of health lifestyles. Our study is also the first to model health lifestyles within settings longitudinally, showing that localized health lifestyles remain largely consistent over time even as individuals flow in and out of these lifestyles. This finding suggests that health lifestyles reflect a range of normative options and bolsters theoretical foundations for the structural significance of health lifestyles.

Friendship Network Processes and Health Lifestyles

This study demonstrates strong evidence that network processes are an important facet of adolescent health lifestyle development. Our results show strong observed network assortativity, which is the result of both peer influence and homophilous selection processes. Whereas previous theorization of health lifestyles articulated the likely role of peer processes in their development and maintenance (Cockerham 2005), these processes had not been previously empirically tested. Documenting peer influence on health lifestyles supports the group-level nature of health lifestyle theorization—with peer group members influencing one another's health lifestyles—whereas previous research has tended toward individual-level measurement. Homophilous selection, whereby adolescents form or dissolve friendship ties based on health lifestyles, was particularly strong. This finding is in line with previous research demonstrating that health lifestyles are a form of status signaling and distinction that shape social ties and social capital (Mollborn, Rigles, and Pace 2021). Homophilous selection also highlights the importance of agency for health lifestyle formation given that adolescents selected friendships on the basis of others' health lifestyles.

This study contributes to an increasing consideration of whether homophilous selection (Lewis and Kaufman 2018) and/or peer influence (Goldberg and Stein 2018) may operate over other clusters of behaviors or attitudes rather than for single behaviors at a time (Strang and Soule 1998). Links between networks and single behaviors have longstanding theoretical and empirical bases, and shifting the paradigm toward clusters will not be easy. However, our results suggest such a shift can produce meaningful and useful results. As one of the first investigations of network selection and influence on clusters of behaviors (see also adams et al. 2020), our approach complements existing strategies focused on individual behaviors. However, many mechanisms underpinning social influence may work equally well for clusters of behaviors as for individual behaviors.

Focusing on the link between networks and single characteristics simplifies methodological strategies (e.g., it is easier to collect data that focus on a single domain at a time, statistical frameworks are more parsimonious, etc.). Modeling clusters of behaviors, although theoretically supported, may not be methodologically expedient for many researchers. An important step will be to develop tests to compare network characteristics and effects for individual characteristics versus clusters of behaviors as competing models. In such efforts, researchers should not assume that all clusters of behaviors will exhibit similar network effects to what we observe for health lifestyles. Health lifestyles have a robust theoretical and empirical underpinning for their composition and construction. Therefore, researchers should focus on clusters with similarly firm conceptual foundations rather than indiscriminately looking for network effects on other clusters.

Limitations and Future Research

As the first study to identify network processes for health lifestyles, these analyses raise futher questions that are unanswerable with our data, providing future opportunities for health lifestyles and network research. Unfortunately, these analyses' need for a combination of health and complete network data over multiple waves sets a high bar for data requirements, which few studies achieve. Rather than lamenting data limitations, we hope our work spurs a continued expansion of data of this sort, spanning different temporal and spatial contexts (e.g., Franken et al. 2016; Moody et al. 2010). We found both similarities and differences in the health lifestyles and network effects in two schools with vast racial-ethnic, socioeconomic, and geographic differences, bolstering our expectations that future extensions will find informative and interesting patterns. We encourage researchers to further document and explain how and why lifestyles differ across contexts.

We encourage future research to explore heterogeneity in dynamic network processes, including whether the processes differ across lifestyle types. For example, the composition of classes differed by gender in Sunshine, with more girls in the discordant class. Future work could seek to identify whether such differences are driven by network processes. It may also be that different compositions across contexts (e.g., varied distributions of the same health lifestyles) may differentially alter the class-specific nature of peer influence and homophilous selection effects (adams and Schaefer 2016; McFarland et al. 2014; Mollborn et al. 2021).

CONCLUSION

Our study demonstrates that health lifestyles and adolescent peer network processes are deeply intertwined, with each shaping the other to some extent. This study combined group-based clusters of behaviors with network processes to understand how health lifestyles, a meaningful and important concept in social research, develop in specific settings. Our results demonstrate the salience of health lifestyles for adolescent development and friendship networks, with important implications for conceptualizing and modeling peer network processes more broadly. An important consideration is whether the attributes that are diffusing and/or selected are individual (e.g., behaviors, attitudes, etc.) versus collective in nature (e.g., lifestyles). We encourage future consideration of how contextual features or other population characteristics (e.g., sociodemographic composition) may moderate how such peer network processes play out across local settings. Bringing together these theoretically and methodologically advanced ideas will further our understanding of how and why individuals adopt different behaviors.

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SUPPLEMENTAL MATERIAL

Figures A1 and A2 and Tables A1 through A3 are available in the online version of the article.

NOTES

1. We conceptualize local contexts as schools because these are primary normative and behavioral environments for adolescents. Alternative conceptualizations (and modeling approaches) may be appropriate for other populations.
2. *Saturated* indicates that the survey was targeted to the complete student body, providing information on complete peer networks. The saturated design was used for more than 100 schools at the Wave I in-school survey and 16 schools for two additional in-home waves. The two schools we studied were larger and had more complete network data than the other 14 schools with longitudinal network data.
3. Alternate specifications estimated latent class analysis (LCA) restricted to the analytic sample used in the stochastic actor-based models (SABMs) with substantively similar results. We chose to estimate LCA for the full sample given the collective nature of health lifestyles.
4. Despite identifying these indicators within behavioral domains, model estimation does not assume statistical dependency between items within the same domain.

5. We present the fit statistics for the first eight of these in Table A1 in the online version of the article.
6. We also fit LCA models enforcing consistency across the waves (i.e., collapsing estimation across waves) as a robustness check. This approach resulted in similar LCA classes for Jefferson, whereas Sunshine exhibited a four-class best fitting solution. SABM results using these alternate LCA specifications for modeling the focal homophilous selection and peer influence effects were substantively similar to those presented in Figure 3.
7. The normalization and standardization are for presentation purposes only. LCA models were fit on untransformed behavioral indicators.
8. By Wave II, this difference remained in the same direction but diminished in magnitude.
9. These findings are suggestive of potentially important contextual differences in health lifestyle composition. However, more systematically comparing contextual compositional differences requires a larger sample of saturated schools than is available in Add Health (N = 16).
10. We also performed ancillary analyses to examine whether LCA class assignment, or changes, hinged on a select set of behavioral indicators. These analyses showed that attempting to "explain" the changes observed in LCA class assignment—and transitions between classes—depended on multiple behavioral differences/changes and was not attributable to single (or even a small subset of) behaviors. These results further support our focus on health lifestyles rather than on individual behaviors.
11. Although adolescents had the opportunity to nominate friends from outside the school, those nominations are excluded from our analysis because we have no information on their attributes.
12. The general rule of thumb is a Jaccard index greater than .2 is necessary for proper estimation (Snijders et al. 2010).
13. This index provides the properly conditioned form for asking how assortative ties are, given the general tendency for ties to form and the distribution of the attribute in the network (Bojanowski and Corten 2014).

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Peer Network Processes in Adolescents' Health Lifestyles

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These supplementary materials accompany our paper "Peer Network Processes in Adolescents' Health Lifestyles." Here, we provide the full model results from which the figures in the paper are drawn (for both the LCA and SAB models) and elaborate effects in the full model results beyond the focal effects interpreted in the paper.

Full Results, Fit Statistics & Interpretation of Controls

LCA Results

As mentioned in the primary manuscript, Table A1 presents the fit statistics for various class specifications of the Latent Class Analysis (LCA) models separately for each school. Table A2 presents the full set of class-conditional response probabilities from the best fitting of these models.[1]

To summarize these values in the main text, we converted the *rho*s in Table A2 to a set of radar plots, which modified the class-specific probabilities in two ways. First, we normalized each variables' values into a single index ranging from 0-1.[2] Second, we reverse coded indicators as necessary to ensure all normalized values had the healthiest category coded as '1'

[1] The LCA results corresponding to the 2-class solution for Sunshine Wave II are available from the third author on request.

[2] For dichotomous variables, these merely take the probability of LCA class-members having the variable present. For trichotomous variables, we multiplied the category specific response probabilities by a scaling factor (0, 0.5, 1) to reflect the proportion of members in each class who are likely to select the highest category on each variable. For the sexual activity variable, no sex is the lowest category, sex with a condom the middle category, and sex without a condom the highest level.

and the least healthy category coded as '0.'[3] As noted in the main text, this normalization and reverse-coding was for presentation purposes only and was not used in the LCA fitting process.

SAB Model Fit

We considered the standard tests of network fit, which consist of how well the model is able to reproduce the observed Wave II distributions of global features not explicitly modeled (i.e., distributions of indegree, outdegree, geodesic distances and the triad census; Ripley et al. 2019, Snijders, van de Bunt and Steglich 2010). The violin plots presented in panels 1-4 of Figures A1 and A2 show how well the distribution of these network features, as derived from simulations of network and LCA class evolution based upon the fitted model (i.e., the "violins"), corresponded with what was observed at Wave II (red points).

Additionally, to evaluate fit of the behavior (LCA) function, we assessed the distribution of actors across classes, and how well the model recreated the assortativity between friends' LCA classes at Wave II, by measuring the proportion of friendships falling into each of the 9 combinations of ego LCA class and alter LCA class (i.e., same and different LCA classes). The violin plots in panels 5 and 6 of Figure A1 and A2 respectively show how well the model reproduced the number of members of each LCA class, and the mixing patterns between those classes.

In combination, these tests provide assurance that the estimated models were sufficiently able to recreate changes in characteristics of the observed networks and LCA class memberships.

[3] This required subtracting the results of step 1 from zero for the following variables: smoking, drinking, chewing tobacco, drug use, screen time, and sexual activity.

Control Effects

It is worthwhile to interpret the additional effects in the behavior function, since the model relies on a two-mode behavior function that is less commonly used and may be unfamiliar to readers. To begin, the outdegree effect represents the probability of selecting a class, net of other model effects. Like the outdegree effect in the network function, it is negative, suggesting that having or adding ties is costly and unlikely to be done unless other model effects are at work. The two "Outdegree * LCA Class" interactions reflect the likelihood of adolescents adopting each class, relative to the healthy class. Estimates indicate that net of other effects in the model, adolescents were least likely to adopt or stay in the discordant class and most likely to adopt or stay in the unhealthy class. In combination these effects represent the distribution of memberships across classes (similar to the linear and quadratic effects with a traditional SABM behavior function).

The final effects in the behavior function refer to how individual attributes affected class membership. We included a main effect for each attribute, which represents the likelihood of choosing the healthy class, while interactions for the discordant and unhealthy classes represent deviations from the main effect. For example, the female effects in Sunshine indicate that when considering which LCA class to adopt, females were more likely to prefer the discordant class over the healthy class than were males. Additional effects in Sunshine indicate that older students were increasingly likely to choose the discordant class; Asian students were more likely than white students to choose the healthy class, and less likely than white students to choose the discordant or unhealthy classes; and higher GPA students were more likely to adopt the healthy class, and less likely to adopt the unhealthy class. We also observe a marginally significant effect whereby Black students were less likely to belong to the discordant class than white students. In Jefferson, the only significant effects related to GPA. Like Sunshine, higher GPA students were more likely to choose the healthy class and less likely to choose the unhealthy class, compared to lower GPA students.

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Appendix Tables

Table A1. Fit Statistics for LCA, by School and Wave

	Classes	Adj-BIC	Log-Likelihood	G^2	AIC
Jefferson Wave I	2	2419	-6343	2309	2371
	3	2390	-6301	2223	2317
	4	2401	-6278	2178	2304
	5	2422	-6260	2141	2299
	6	2450	-6245	2113	2303
	7	2476	-6230	2082	2304
	8	2510	-6219	2060	2314
Jefferson Wave II	2	2013	-4750	1912	1974
	3	1973	-4703	1819	1913
	4	1980	-4680	1773	1899
	5	1997	-4663	1738	1896
	6	2014	-4645	1703	1893
	7	2037	-4631	1673	1895
	8	2059	-4615	1643	1897
Sunshine Wave I	2	2818	-12230	2685	2747
	3	2815	-12195	2615	2709
	4	2835	-12171	2566	2692
	5	2844	-12141	2507	2665
	6	2868	-12119	2462	2652
	7	2903	-12102	2429	2651
	8	2942	-12088	2400	2654
Sunshine Wave II	2	2450	-8420	2329	2391
	3	2453	-8390	2270	2364
	4	2473	-8368	2226	2352
	5	2490	-8346	2181	2339
	6	2518	-8328	2147	2337
	7	2551	-8313	2117	2339
	8	2582	-8298	2085	2339

Table A2. Class Conditional Response Probabilities from Latent Class Analyses, by School and Wave

	Jefferson, Wave I			Jefferson, Wave II			Sunshine, Wave I			Sunshine, Wave II		
	Healthy	Mixed	Unhealthy	Healthy	Mixed	Unhealthy	Healthy	Mixed	Unhealthy	Healthy	Mixed	Unhealthy
Smoking												
None	0.86	0.31	0.12	0.81	0.43	0.07	**0.95**	**0.95**	0.44	0.96	**0.94**	0.40
Infrequent	0.10	0.40	0.13	0.13	0.43	0.10	0.06	0.00	0.30	0.04	0.05	0.33
Frequent	0.05	0.30	0.75	0.06	**0.13**	0.83	0.00	**0.05**	0.26	0.00	**0.01**	0.27
Drinking												
None	0.57	0.13	0.09	0.65	0.20	0.15	0.77	**0.42**	0.11	0.87	0.76	0.22
Moderate	0.20	0.07	0.08	0.14	0.00	0.05	0.08	0.36	0.04	0.05	0.08	0.10
Heavy/Problem	0.23	0.80	0.82	0.22	0.80	0.80	0.15	**0.23**	0.86	0.08	**0.16**	0.68
Other Tobacco Use	0.02	0.48	0.15	0.02	0.32	0.23	**0.02**	0.01	0.07	0.07	0.00	0.06
Drug Use	0.02	0.37	0.61	0.03	0.27	0.52	0.02	**0.17**	0.55	**0.03**	0.02	0.51
Physical Activity												
Heavy	0.38	0.64	0.18	0.27	0.61	0.17	0.30	0.33	0.28	0.56	0.01	0.25
Moderate	0.27	0.18	0.38	0.33	0.31	0.34	0.34	0.25	0.36	0.31	0.33	0.32
Light	0.35	0.18	0.45	0.40	0.08	0.49	0.36	0.41	0.36	0.13	0.67	0.44
Screen Time												
Low	0.51	0.57	0.60	0.63	0.66	0.56	0.37	0.63	0.39	0.44	0.43	0.43
Moderate	0.30	0.23	0.22	0.17	0.24	0.25	0.34	0.12	0.32	0.28	0.32	0.29
High	0.19	0.19	0.18	0.20	0.10	0.19	0.30	0.25	0.29	0.28	0.24	0.29
Sexual Activity												
None	0.82	0.38	0.15	0.79	**0.60**	0.17	0.75	0.24	0.25	0.73	**0.65**	0.30
Condom @ last sex	0.12	0.51	0.40	0.14	0.38	0.48	0.14	0.53	0.34	0.19	0.17	0.39
No Condom @ last sex	0.06	**0.11**	0.45	**0.07**	0.02	0.35	0.12	0.23	0.41	0.08	0.19	0.30
Health Care Use	0.52	0.62	0.48	0.49	0.80	0.44	0.38	0.54	0.33	0.45	0.25	0.38
Sufficient Sleep	**0.74**	0.84	0.55	**0.75**	0.79	0.62	0.70	0.56	0.58	0.80	0.56	0.55
Regular Seatbelt Use	0.70	0.44	0.39	0.75	**0.64**	0.36	**0.75**	0.80	0.52	**0.71**	0.77	0.56
Distribution	**0.49**	**0.19**	**0.33**	**0.41**	**0.19**	**0.40**	**0.53**	**0.15**	**0.32**	**0.26**	**0.35**	**0.39**

"Heat map" legend: Dark gray = least healthful class for that indicator; light gray = significantly (p < .05) less healthy than than sample mean; bold = significantly more healthy than sample mean; underlined= most healthy class for that indicator; white = not significantly different from sample mean, or row not coded (middle categories).

Table A3. SABM Parameters, by School

	Jefferson			Sunshine		
	b	SE		b	SE	
Behavior Function (LCA Class)						
Friend w/ same LCA Class [a]	**0.429**	**0.098**	***	**0.260**	**0.096**	***
Outdegree	-1.146	0.187	***	-0.505	0.112	***
Outdegree * LCA Discordant Class [b]	-0.561	0.215	***	-0.368	0.120	***
Outdegree * LCA Unhealthy Class [b]	0.692	0.194	***	0.210	0.167	
Female	-0.084	0.241		-0.511	0.170	***
Female * LCA Discordant	-0.347	0.414		1.128	0.304	***
Female * LCA Unhealthy	0.247	0.376		0.375	0.294	
Age	0.035	0.132		-0.103	0.103	
Age * LCA Discordant	-0.111	0.207		0.308	0.109	***
Age * LCA Unhealthy	0.070	0.198		0.019	0.126	
Hispanic [c]	-	-		0.240	0.305	
Hispanic * LCA Discordant	-	-		-0.631	0.423	
Hispanic * LCA Unhealthy	-	-		-0.259	0.369	
Black	-	-		0.222	0.315	
Black * LCA Discordant	-	-		-0.632	0.384	†
Black * LCA Unhealthy	-	-		-0.259	0.369	
Asian/PI	-	-		0.612	0.301	*
A/PI * LCA Discordant	-	-		-0.820	0.380	*
A/PI * LCA Unhealthy	-	-		-0.910	0.382	**
GPA	0.365	0.186	*	0.304	0.095	***
GPA * LCA Discordant	0.225	0.326		-0.064	0.164	
GPA * LCA Unhealthy	-1.266	0.292	***	-0.829	0.157	***
Parental Education	0.045	0.143		-0.131	0.084	
Parental Education * LCA Discordant	0.093	0.222		0.189	0.122	
Parental Education * LCA Unhealthy	-0.312	0.210		0.162	0.099	
Rate	1.452	0.115	***	2.583	0.183	***
Network Function						
LCA (same category) [d]	**1.008**	**0.117**	***	**3.159**	**1.435**	***
Outdegree	-3.890	0.292	***	-6.996	0.863	***
Reciprocity	2.735	0.119	***	3.882	0.346	***
Transitive Triplets	0.829	0.052	***	1.793	0.304	***
Transitive Triplets * Reciprocity	-0.747	0.073	***	-1.631	0.355	***
Indegree – Popularity (sqrt)	0.372	0.142	***	0.055	0.321	
Outdegree – Popularity (sqrt)	-0.757	0.110	***	-1.172	0.246	***
Indegree – Activity (sqrt)	0.150	0.078	†	0.055	0.420	
Course Overlap[e]	0.765	0.087	***	2.168	0.450	***
Extracurricular Activity Overlap[e]	0.253	0.076	***	0.379	0.200	†

[cont'd on next page]

[Table 3 continued]

Homophilous Selection[f]						
Gender (same category)	0.162	0.047	***	0.476	0.091	***
Grade-level (similarity)	0.698	0.081	***	0.590	0.080	***
Race (same category)	-	-		1.296	0.111	***
GPA (similarity)	0.669	0.129	***	0.590	0.080	***
Parental Education (similarity)	0.312	0.127	**	0.446	0.234	†
Attribute-Based Popularity[g]						
Grade-level	-0.008	0.032		0.356	0.104	***
GPA	0.000	0.034		0.256	0.106	*
Parental Education	0.099	0.029	***	0.003	0.050	
Rate	12.694	0.668	***	4.989	0.665	***

*** p<0.001, ** p<0.01, *p<0.05, †p<0.10

NOTES

[a] Specified using the "to" shortname within RSiena.

[b] Reference category for the LCA Class and LCA Class-based interactions is the Healthy class.

[c] Reference category for race/ethnicity variable is non-Hispanic white.

[d] Specified using the "from" shortname within RSiena.

[e] Measured at the dyadic level and specified using the "X" shortname within RSiena.

[f] Homophilous selection was operationalized differently for continuous attributes, which use a rescaled function of absolute difference, and categorical attributes, where dyad members are designates as either 1=same or 0=different. RSiena shortnames are in parentheses.

[g] Specified using the "altX" shortname within RSiena.

Figure A1. SABM Goodness of Fit Statistics, Jefferson High School

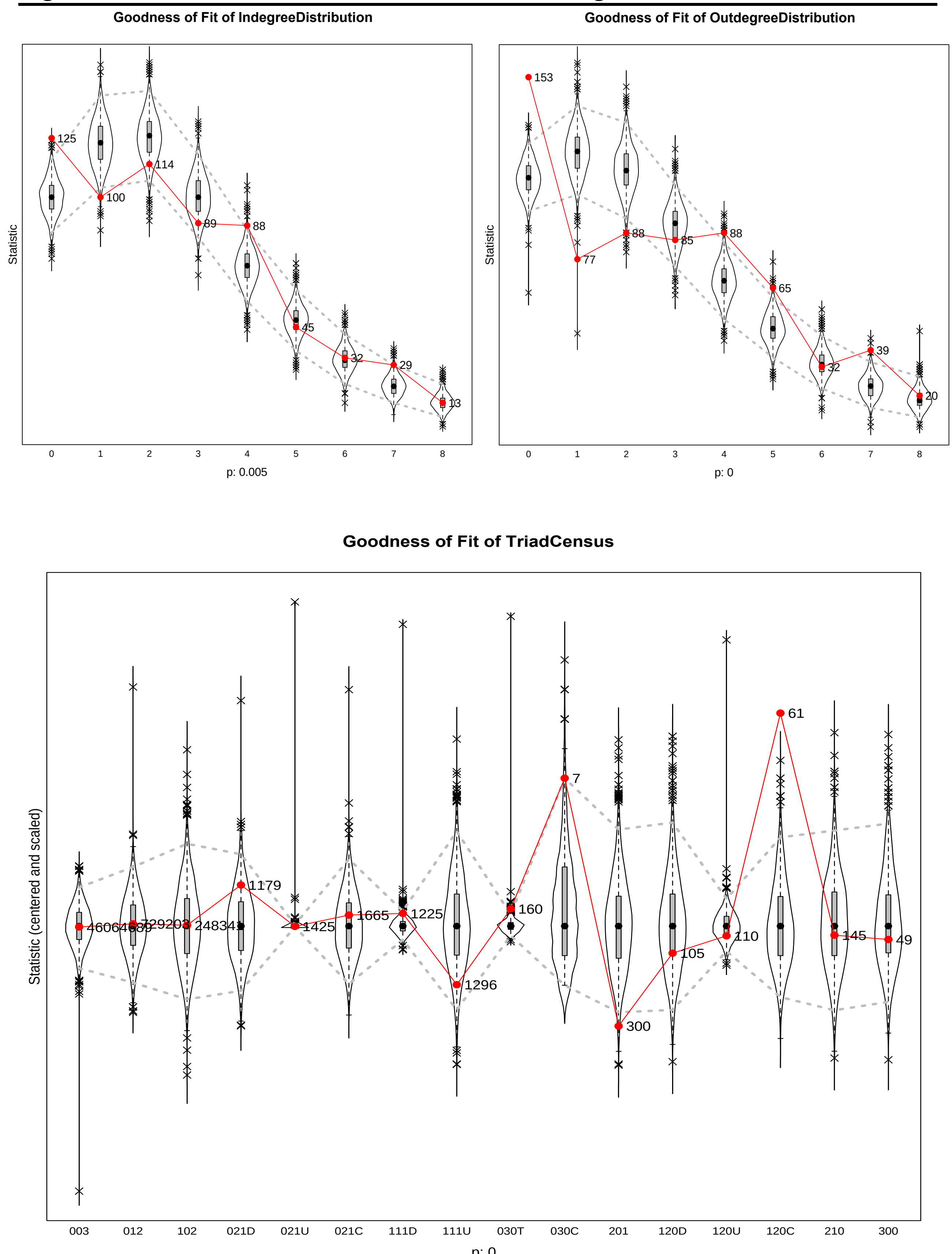


Figure A1. SABM Goodness of Fit Statistics, Jefferson High School (cont'd)

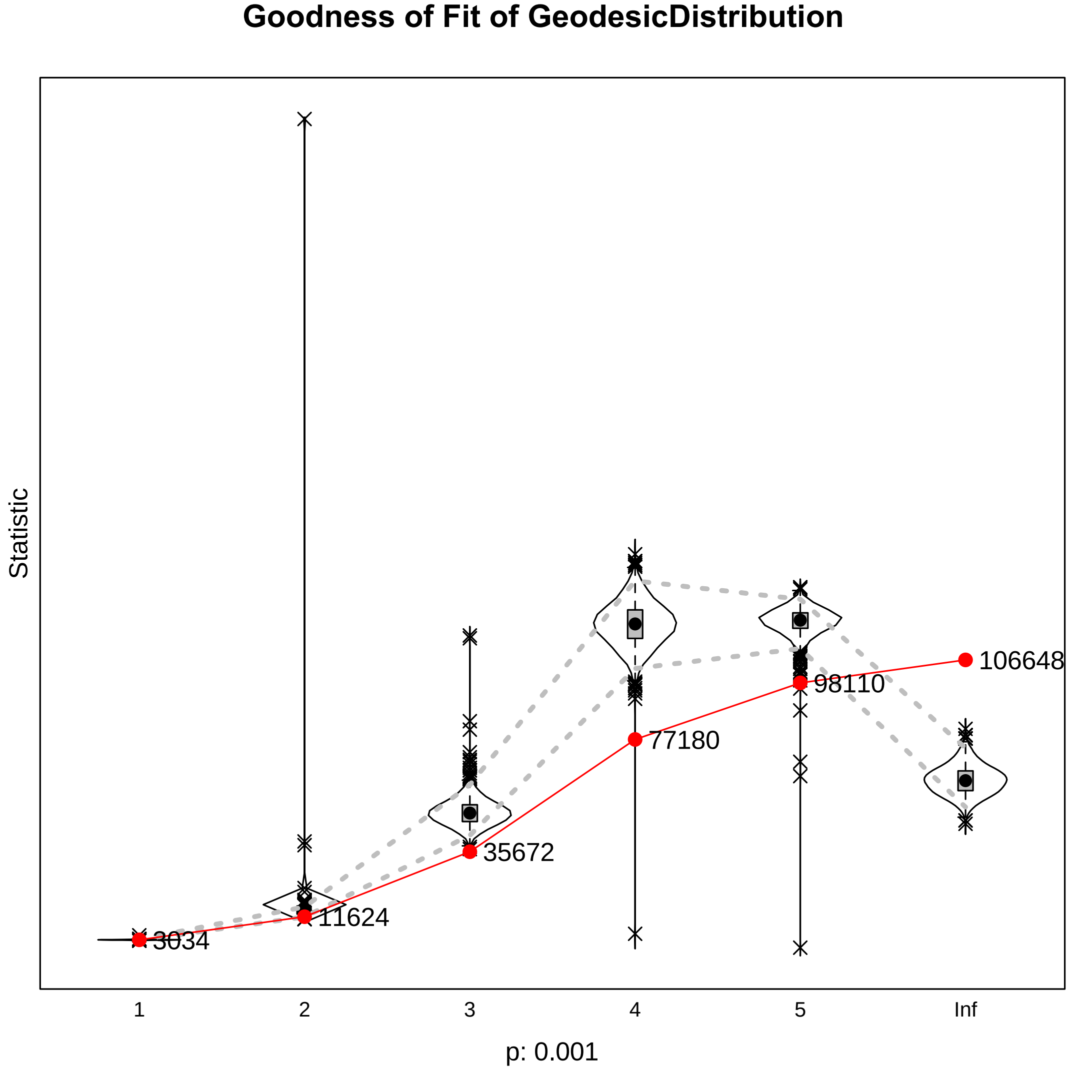
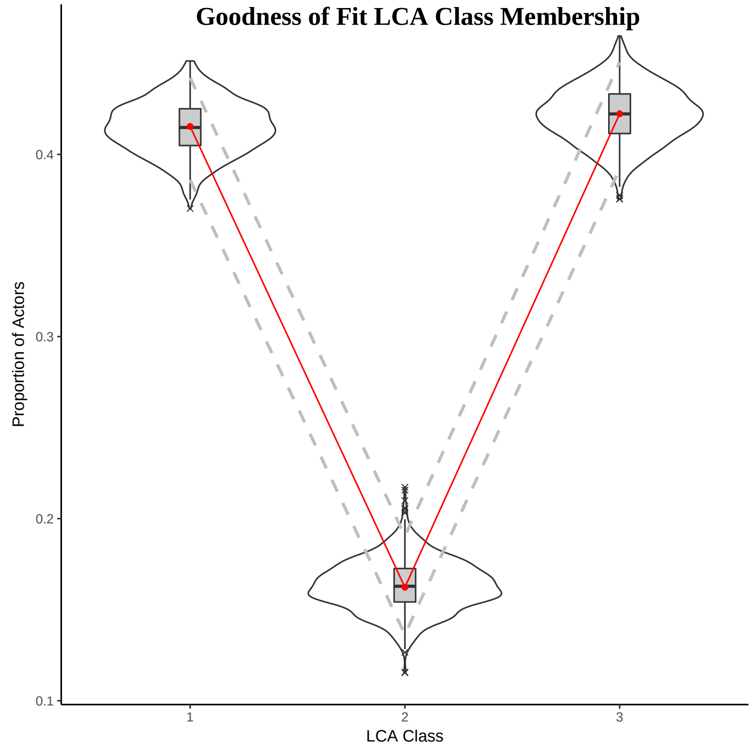


Figure A1. SABM Goodness of Fit Statistics, Jefferson High School (cont'd)



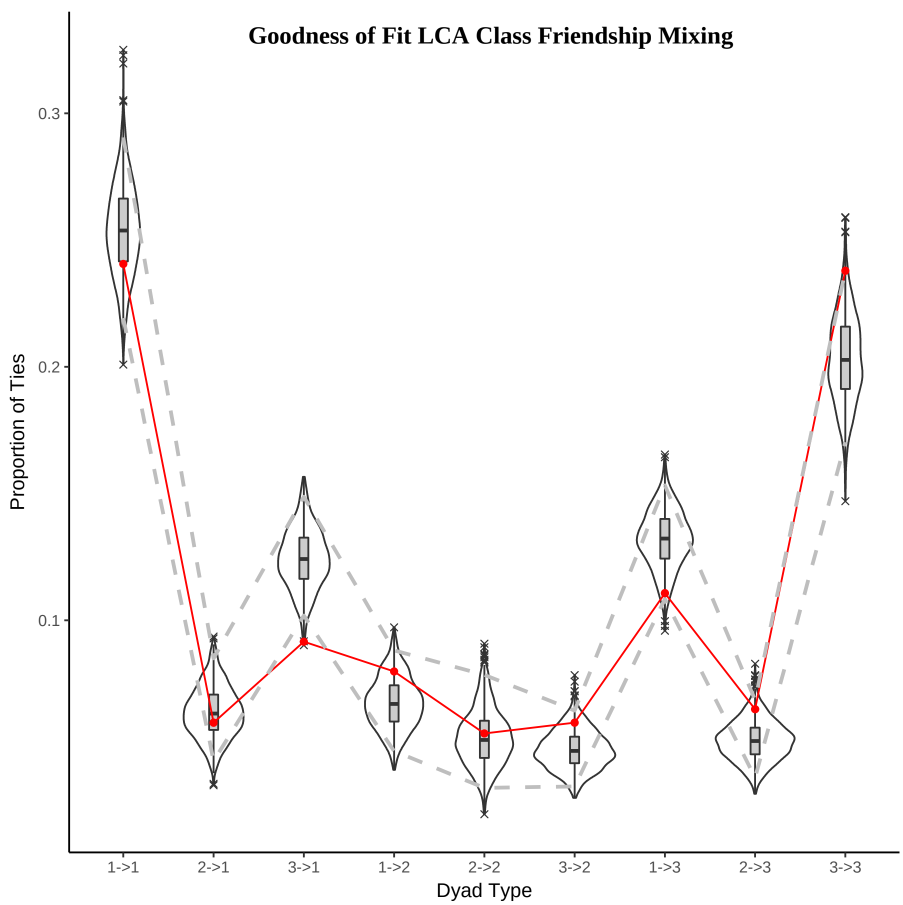


Figure A2. SABM Goodness of Fit Statistics, Sunshine High School

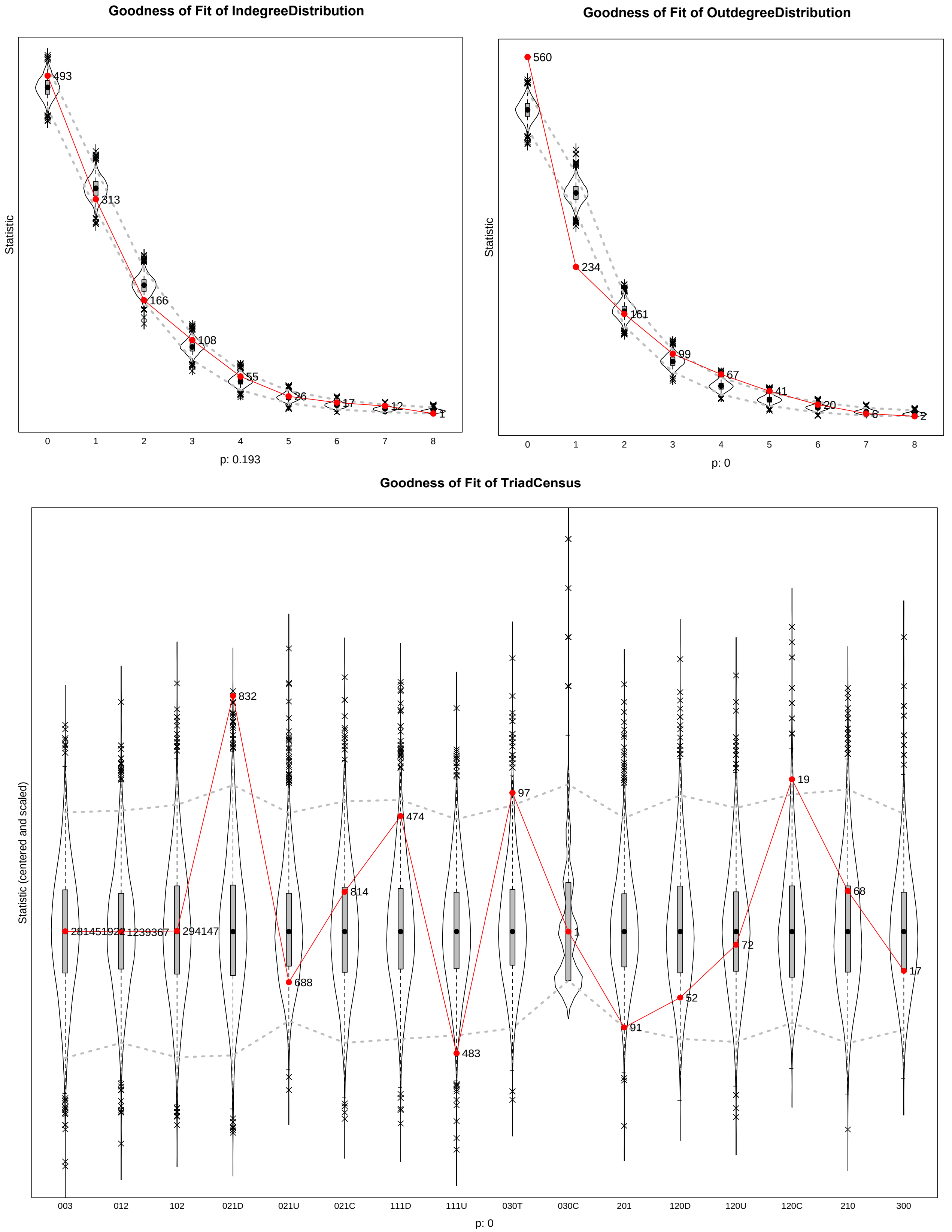


Figure A2. SABM Goodness of Fit Statistics, Sunshine High School (cont'd)

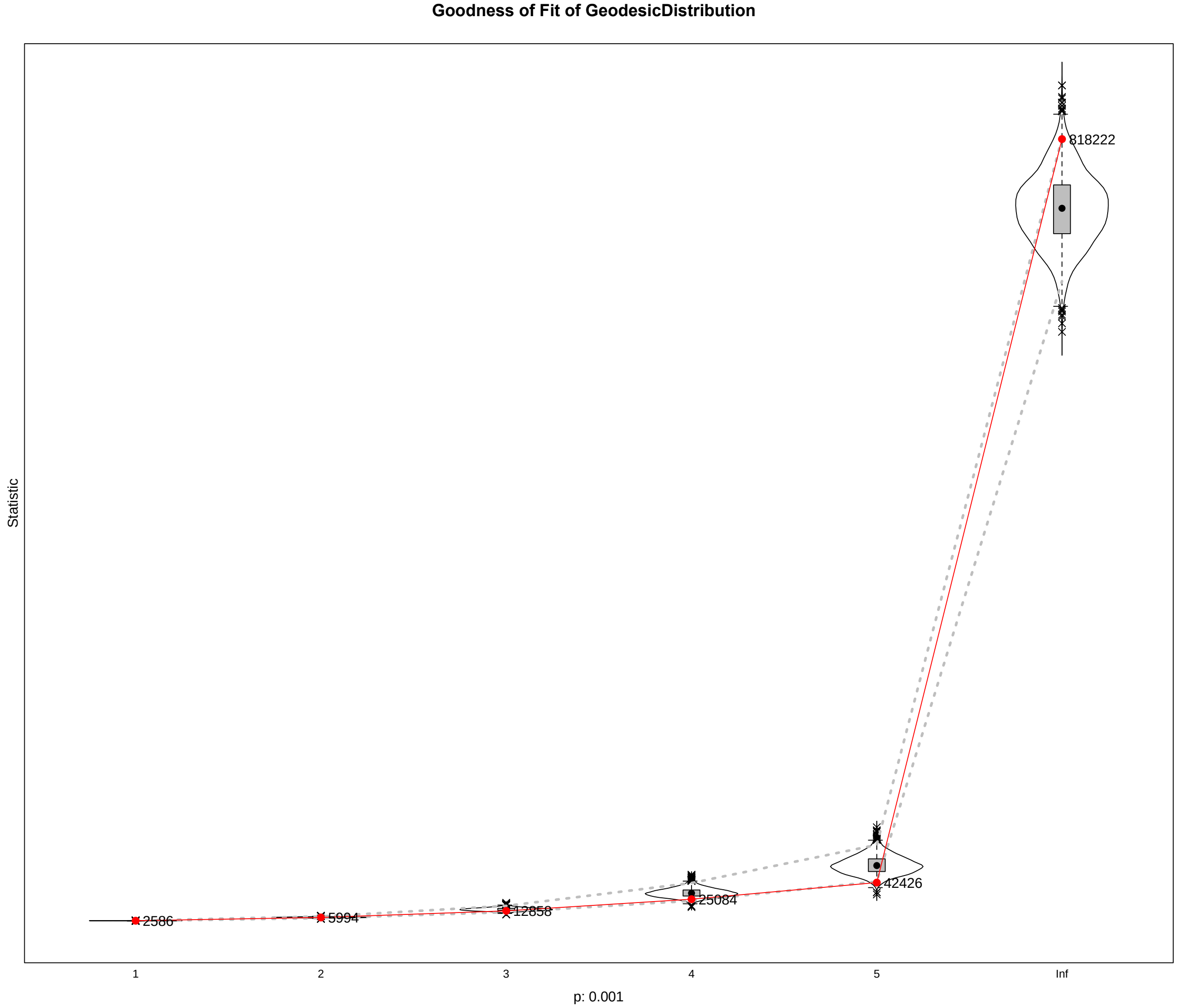


Figure A2. SABM Goodness of Fit Statistics, Sunshine High School (cont'd)