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REGULAR ARTICLE

Multiple Health Risk Behaviors in Young Adult Smokers: Stages of Change and Stability over Time

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Abstract

Background Health risk behaviors (HRBs) are common, yet not well understood in young adult smokers.

Purpose We examined HRB profiles over 12 months in young adult smokers participating in a Facebook smoking cessation intervention clinical trial.

Methods Participants (N = 500; age M = 20.9 years; 54.6% women) were recruited online and randomized to receive either a 3-month Facebook smoking cessation intervention or referral to Smokefree.gov (control). A Health Risk Assessment determined risk for 10 behaviors at baseline and 3, 6, and 12 months. Latent class analysis (LCA) and latent transition analysis (LTA) were used to identify patterns of HRBs and changes over time.

Results At baseline, participants reported an average of 5.4 (standard deviation [SD] = 1.7) risk behaviors, including smoking (100%), high-fat diet (84.8%), poor sleep hygiene (71.6%), and low fruit and vegetable intake (69.4%). A 3-class model fit the data best at baseline and all follow-up time points: *low risk* (28.8% at baseline) with low likelihood of risk on all behaviors except smoking, *substance use risk* (14.0% at baseline) characterized by heavy episodic drinking, cannabis use, and other illicit drug use, and *metabolic risk* (57.2% at baseline), with a high percentage of members at risk for a low fruit and vegetable intake, high-fat diet, inactivity, stress, and poor sleep hygiene. Classes were very stable at 3, 6, and 12 months, with few participants transitioning between classes.

Conclusions Most young adult smokers engaged in multiple risk behaviors, with meaningful clustering of behaviors, and demonstrated stability over a year's time. In addition to smoking, targets for intervention are co-occurring substance use and metabolic risk behaviors.

Clinical Trials Registration NCT02207036.

Keywords Multiple health risk behavior • Intervention • Social media • Young adults • latent transition analysis

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Lifestyle behaviors are leading contributors to preventable morbidity and mortality worldwide [1]. Among the top 20 risk factors are smoking, alcohol and drug use, poor diet, and physical inactivity [2]. In the USA, health risk behaviors (HRBs) are common among all age groups [3–5] with increased mortality [6] and substantial costs for the health care system [7]. A majority of U.S. adults meet criteria for multiple HRBs, and among smokers, 97% carry at least one additional risk behavior [8, 9]. Even in young adulthood, individuals who engage in multiple HRBs are at increased risk for cardiovascular disease [10], underscoring the importance of identifying high-risk groups and potentially high-yield behavioral targets.

The co-occurrence of multiple HRBs within individuals is well documented [11–17], developing during adolescence [18, 19] and highly prevalent by young adulthood [14, 20, 21]. For example, 87.5% of German college students reported two or more of the following risks: current smoking, heavy episodic drinking, poor diet, and insufficient exercise [20]. Young adulthood is an ideal time to intervene, as nutrition, physical fitness, and not smoking in young adulthood are associated with better health later in adulthood [22, 23]. Most investigations of HRBs in young adults have used college student samples focusing on alcohol and tobacco co-use [24, 25] or multiple HRBs [20, 21, 26]. Only a few studies have examined clustering of young adults' HRBs outside of the college context. A nationally representative survey of American young adults identified three profiles of HRBs (unhealthy, mixed, and healthy) [27], and a systematic review of studies on the co-occurrence of young adults' multiple HRBs conducted in the UK concluded that smoking, sexual risk behavior, and substance use often cluster [28]. Although these studies measured smoking, they did not focus specifically on smokers. Young adult smokers are more likely to develop negative health consequences such as cardiovascular disease and cancer later in life [10], and such risks may be compounded by co-occurring HRBs [29, 30]. A better understanding of HRB patterns in young adults is needed. HRBs often co-occur and can covary. That is, change in one risk behavior is associated with change in another behavior [31]. Interventions targeting multiple HRBs can result in multiple HRB change among targeted and complementary behaviors [32, 33]. Given that risk behaviors often covary and multiple HRBs may be successfully targeted at once, it is important to understand how HRBs may group together in young adult smokers.

In addition to clustering of HRBs, a better understanding of young adult smokers' readiness to change HRBs is needed to inform intervention design. Research suggests that interventions targeting multiple HRBs show promise and may be more beneficial with regard to public health impact than interventions focusing on single risk behaviors [34]. However, when readiness to change multiple HRBs is generally low, excessive behavioral targets demanding action may increase participant resistance and decrease intervention effectiveness [35]. The Transtheoretical Model (TTM) conceptualizes the process of change as proceeding through five stages [36]: precontemplation (not ready to change in the near future), contemplation (intending to change within the next 6 months), preparation (intending to change within the next 30 days), action (achievement of change goal for less than 6 months), and maintenance (achievement of change goal for 6 months or more). The TTM can guide behavior change interventions and may be especially helpful in addressing multiple HRBs [37]. Notably, Keller et al. [20] found that less than a third of college students with multiple HRBs was preparing to change at least one behavior domain and fewer were ready to change multiple risks. Identifying patterns of HRBs and examining stage of change for each behavior may help determine which HRBs should be targeted for direct action and which may require motivational intervention.

Latent variable modeling approaches can be used to examine patterns of HRBs and characterize changes in those patterns over time. Such approaches (e.g., latent class analysis [LCA], latent transition analysis [LTA]) seek to discover the underlying latent structure of discrete (categorical) data, thereby identifying naturally occurring mutually exclusive and exhaustive categories. To understand patterns of smoking, LCA has been used to classify symptoms of nicotine dependence in adult smokers [38] and patterns of smoking among college students based on multiple indicators of smoking behavior [39]. Examining patterns over time, LTA has been used to categorize transitions into and out of stages of smoking as a function of home smoking bans throughout young adulthood [40]. As applied to multiple HRBs among adult smokers with serious mental illness [41], LCA identified three subgroups of risk behaviors: a low-risk group, a global risk group, and a mood and metabolic risk group, characterized by inactivity, unhealthy diet, sleep problems, and poor stress and depression management. LCA has not yet been applied to understand health risk profiles among young adult smokers or to understand patterns of HRBs in young smokers over time. Using both LCA and LTA, this exploratory study identified latent classes of HRBs at each time point before exploring transitions between latent classes.

Understanding patterns of HRBs and stage of change for specific behaviors among young adult smokers is imperative in prioritizing content to be included in future health behavior change interventions for this population. The present study sought to examine risk status, stage of change, and latent profiles of HRBs over 12 months' time in young adult smokers participating in a smoking cessation treatment trial. We hypothesized that health risks other than smoking would be common among young adult smokers and that there would be multiple distinct patterns of health risk among young adult smokers at baseline. We also explored changes in these patterns over time.

Method

Participants and Procedure

Data were taken from a clinical trial testing the efficacy of the Tobacco Status Project, a Facebook quit smoking intervention described previously [42, 43]. Participants were young adults aged 18–25 who had smoked at least 100 cigarettes in their lifetime, currently smoked at least 3 days per week, and used Facebook at least 4 days per week at the time of recruitment. Participants were recruited through a paid advertising campaign on Facebook conducted between October 2014 and August 2015, using a strategy that had been successful previously [44]. Interested participants were screened for eligibility online, and those who answered three questions about the study correctly signed online informed consent, sent proof of identity, completed an online baseline assessment, and were randomized to treatment or control conditions, stratified by daily smoking status (daily/nondaily) and stage of change for quitting smoking (precontemplation, contemplation, or preparation). Control group participants were referred to the National Cancer Institute's online smoking cessation resource, Smokefree.gov. Intervention group participants were assigned to a private Facebook group tailored to stage of change for quitting smoking. The Facebook smoking cessation intervention lasted 3 months and included daily Facebook posts and weekly "Ask the Doctor" sessions (live counseling sessions conducted on Facebook) targeted to stage of change. For those ready to quit in the next month, an optional six-session program of cognitive-behavioral counseling with a study clinician was available using Facebook's "events" feature. Intervention content included brief attention to other HRBs in relation to smoking (e.g., alcohol use, diet, exercise). Participants were contacted by email to complete an assessment at intervention completion (3 months), and again at 6 and 12 months after baseline and were compensated with $20 gift cards for completing each assessment. A total of 500 young adult smokers participated in the study; 71% (354/500) completed HRB measures at 3 months, 65% (323/500) completed at 6 months, and 69% (343/500) completed at 12 months.

Measures

A Smoking Questionnaire [45] assessed average number of cigarettes smoked per day, days smoking per week, the Fagerström Test for Cigarette Dependence (FTCD) [46], and past year quit attempts (dichotomized to yes/no). Demographic characteristics included age, gender, race, sexual orientation, household income, student status, employment status, and educational attainment.

The Staging Health Risk Assessment [47] screened for current risk status (at risk or low risk) and stage of change (precontemplation, contemplation, preparation, action, or maintenance) for 10 HRBs: cigarette smoking, heavy episodic drinking (4+ drinks for women and 5+ drinks for men in a 4 hr period), use of cannabis, use of any other illegal drug or prescription drug outside of a prescribed dosage, condomless sex (only among those not in a relationship), unhealthy diet (high-fat diet and/or overeating), low fruit and vegetable consumption (<5 servings/day), low physical activity (<150 min/week of moderate or greater physical activity), poor sleep hygiene (e.g., irregular bed- and wake-time schedule, <7 hr sleep/night), and poor stress management (e.g., not engaging in relaxation exercises, talking with others, or making time for social activities). For each HRB, participants were categorized as "at risk" or "low risk", then further categorized by stage of change. "At-risk" participants included those in the precontemplation (not ready to change), contemplation (ready to change in the next 6 months), and preparation (ready to change in the next 30 days) stages. "Low-risk" participants included those in the action (meeting guidelines for less than 6 months) or maintenance (meeting guidelines for 6+ months) stages of change. Risk-status criteria were based on Healthy People 2020 goals for the nation [48]. When guidelines included multiple components (e.g., high-fat diet, high-calorie diet), participants were coded as low-risk only when they met the guideline in full. Similarly, stages of change were defined according to readiness to meet the guideline in full (e.g., readiness to eat a diet with appropriate fat *and* calories). The risk definitions and stages of change have been well studied for multiple HRBs in community populations [32, 47, 49, 50] and smoking samples [41, 51].

Analyses

Analyses proceeded in three stages. First, at baseline and 3, 6, and 12 months follow-up, the percent of participants at risk, and the identified preaction stage (i.e., precontemplation, contemplation, preparation) for those at risk, were determined for each HRB. Second, LCA was employed to discern the common patterns of HRBs at each time point. Third, LTA was used to examine the most likely patterns of HRBs over time.

LCA was employed first at baseline, then each follow-up time point for evaluation of structure stability. LCA is a latent variable modeling technique that characterizes homogeneous populations within a larger sample who share common response patterns to categorical indicators (e.g., present/absent). Models of 1–6 classes were fit and standard criteria were used to compare the models [52]. Model selection was based on goodness of model fit, parsimony, and adequacy of the model with respect to the research questions being posed. Four sets of criteria were used for selecting the optimal number of latent classes in factor mixture models as recommended by Muthén and Muthén [53]. First, the Bootstrapped Parametric Likelihood Ratio Test (BLRT) [54] tested for model improvement in each successive model over a model with one fewer class [55]. Second, the Sample Size Adjusted Bayesian Information Criterion (saBIC) [56] and Aikaike's information criterion (AIC) [57] were examined, with lower values indicating better model fit [53, 58]. Third, the entropy value, ranging from 0 to 1, measured the clarity of classification. Entropy values that are close to 1 indicate that a model has clearly identified individuals of different types, and it can be a useful summary measure [53, 59, 60]. Finally, the usefulness of latent classes in practice was evaluated by substantive interpretation of the classes in a given model, as well as the parameter estimates including class membership or posterior probabilities and class-specific conditional response probabilities (CRPs). With LCA, observations are classified into their most likely latent classes on the basis of the estimated posterior probabilities for the observations. High diagonal and low off-diagonal values in the class classification table indicate good classification. CRPs reflect the probability that an individual within a particular class has a high-risk health behavior. Based on the patterns of the estimated conditional probabilities, meaningful labels or definitions of the latent classes were made.

LTA was then used to examine the extent to which patterns of HRBs at baseline were stable over time, using three analyses (baseline–3 months, 3–6 months, and 6–12 months). Detailed statistical presentations of the general LTA framework are available in Humphreys and Janson [61] and Reboussin et al. [62]. LTA is a longitudinal strategy that assesses the probabilistic change in class membership over time with categorical latent variables [63, 64]. This analysis extends LCA by assigning transition probabilities, which are conditional probabilities describing the probability of being in a given state at time = t, conditional on the state at time = $t - 1$. We used an LTA to model the stability of HRBs over the course of 12 months; latent transition probabilities were then used to evaluate how individuals either exhibited the same HRB pattern or changed patterns over 12 months. We hypothesized a priori that the intervention may affect multiple HRBs, because multiple HRBs can occur following interventions aimed at changing a single behavior [65]. Moreover, we found a significant intervention effect on smoking outcomes at 3 months in the RCT [43]. Therefore, the models initially included treatment condition as a covariate. However, because very few participants transitioned between classes over time, adding treatment condition to the model resulted in several empty cells. For example, no participants in the control condition transitioned from substance use risk to low risk between baseline and 3 months. Because adding another parameter (i.e., treatment condition) resulted in several empty cells, the estimates were unstable and could not be reliably interpreted. Moreover, treatment condition was not a significant covariate in the LCA models (ps > .05). Therefore, all models reported here are without the inclusion of treatment condition. LCA and LTA were conducted with Mplus version 7.4 [66] due to the availability of multiple model fit indices not available in other statistics platforms and the ease of employing randomized starting values. Other analyses were conducted with IBM SPSS Statistics. All available cases were used at each time point.

Results

Participant characteristics are presented in Table 1. Heterosexual participants were significantly less likely to complete at least one follow-up (77.8%) compared to nonheterosexuals (88.9%; p = .005); otherwise, attrition did not differ by participant characteristics.

Prevalence of HRBs

Prevalence and stage of change for each of the 10 HRBs in the full sample (i.e., participants who were and were

Table 1. Participant characteristics at baseline (N = 500)

	M (SD)/*N* (%)
Age	20.9 (2.0)
Gender (% female)	273 (54.6%)
Race[a]	
Non-Hispanic White	366 (73.8%)
Native American	5 (1.0%)
African American	13 (2.6%)
Asian/Pacific Islander	6 (1.2%)
Hispanic	34 (6.9%)
More than one	72 (14.5%)
Sexual orientation (% heterosexual)[b]	366 (73.2%)
Household income	
Less than $20,000	144 (28.8%)
$21,000–$60,000	245 (49.0%)
$61,000–$100,000	77 (15.4%)
More than $100,000	34 (6.8%)
Student status (% currently in school)	152 (30.4%)
Employment status (% currently employed)	316 (63.2%)
Education	
High school degree or less	240 (48.0%)
Some college	231 (46.2%)
College degree or higher	29 (5.8%)
Daily smoking (% daily smokers)	433 (86.6%)
Cigarettes per day	11.6 (6.8)
FTCD score	3.2 (2.1)
Past year 24 hr quit attempt (% yes)	311 (62.2%)

[a]Race was dichotomized to non-Hispanic White versus all other races for comparison of demographic characteristics between baseline latent classes.

[b]Heterosexuals were significantly less likely to complete at least one follow-up than nonheterosexuals.

FTCD Fagerström Test of Cigarette Dependence.

not at risk) are presented in Fig. 1. The mean number of risk behaviors over time was 5.4 (standard deviation [*SD*] = 1.7, range: 1 to 10) at baseline, 5.0 (*SD* = 1.9, range: 0 to 10) at 3 months, 4.8 (*SD* = 2.0, range: 0 to 10) at 6 months, and 4.7 (*SD* = 2.1, range: 0 to 10) at 12 months. The most frequent risks at all time points were smoking, high-fat diet, low fruit and vegetable consumption, and poor sleep hygiene. The least frequently

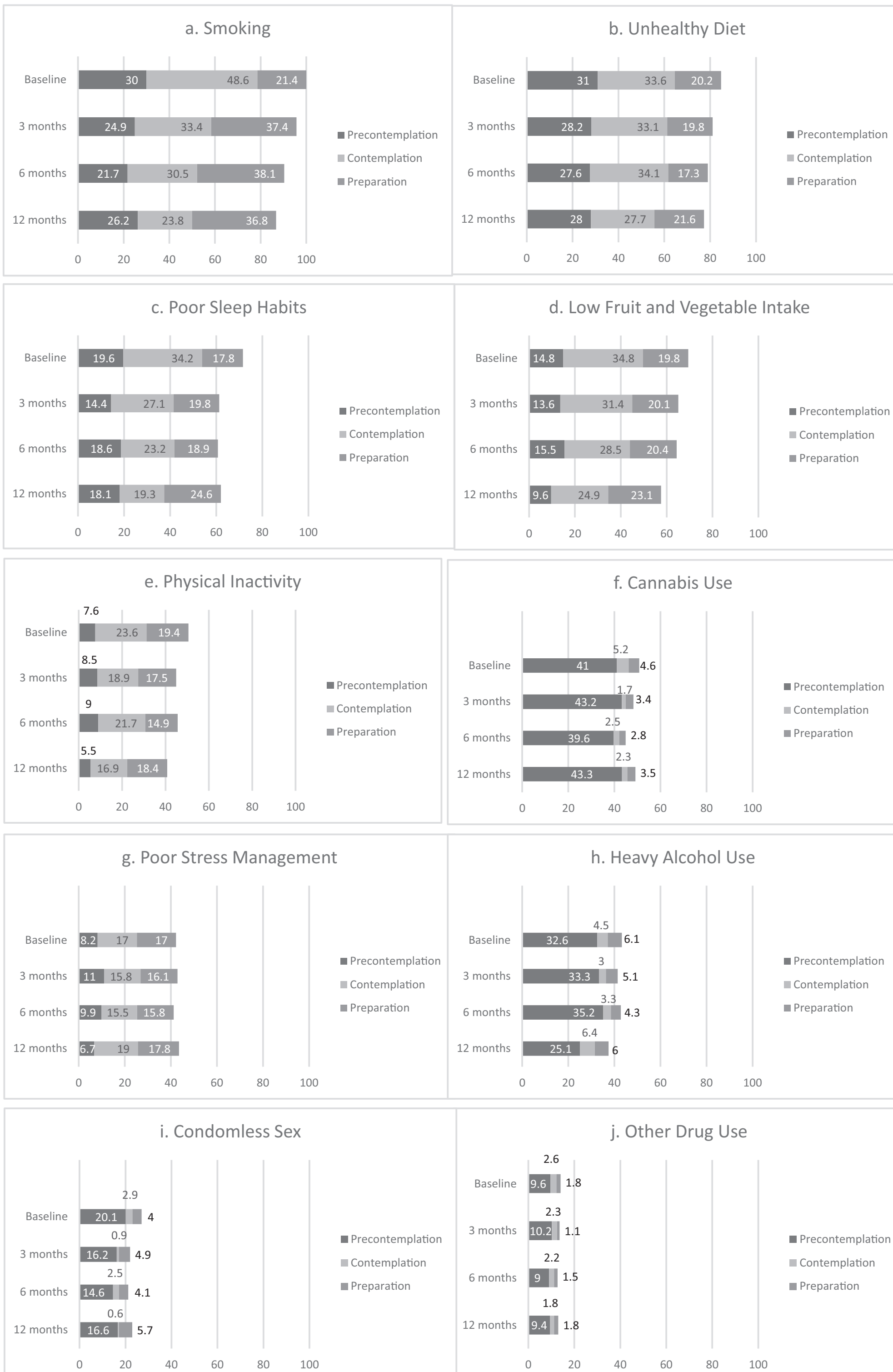

Fig. 1. Proportion of participants at-risk and in each preaction stage of change (precontemplation, contemplation, and preparation) for 10 health risk behaviors reported at baseline, 3, 6, and 12 months.

reported were heavy drinking, condomless sex, and drug use.

Stage of Change for HRBs

At baseline, participants at risk were most ready to change their stress management, physical activity, and fruit and vegetable consumption, compared to other HRBs. At all follow-ups, participants at risk were most ready to change smoking, stress management, and physical activity. Across all time points, participants at risk were least ready to change heavy drinking, cannabis use, and other drug use. Percentages ready to change each behavior, among those at risk, are presented in Table 2.

Latent Class Model Selection

Using LCA, models between 1 and 6 classes were fit for baseline and each follow-up time point (Table 3). At all four time points, relatively lower saBIC and AIC values and significant BLRT values favored the 3-class solutions over the other solutions.

Table 4 shows the average latent class probabilities for being assigned to a specific latent class at each time point. The values on the diagonal are high and the values off the diagonal are low, indicating a good quality of classification. The entropy values of .59 to .70 indicate a fairly clear classification at each time point.

Latent class probability and class definitions

CRPs for the 3-class model at each time point are presented in Fig. 2. One class represented those who were most likely to be at risk for alcohol, cannabis, and other drug use and was labeled *substance use* (14.0% at baseline, 19.8% at 3 months, 24.8% at 6 months, and 12.5% at 12 months). A second class represented those who were most likely to be at risk for an unhealthy diet, low fruit and vegetable consumption, poor sleep habits, poor stress management, and physical inactivity and was thus labeled *metabolic* (57.2% at baseline, 54.2% at 3 months, 47.7% at 6 months, and 51.3% at 12 months). A third class had the lowest likelihood of risk for all HRBs, and was labeled *low risk* (28.8% at baseline, 26.0% at 3 months, 27.6% at 6 months, and 36.2% at 12 months).

Characteristics of Latent Classes

We examined characteristics (listed in Table 1) associated with membership in each latent class at baseline. Gender (χ^2 = 9.78, p = .008), daily smoking (χ^2 = 7.04, p = .030), cigarettes per day (F[2, 497] = 5.14, p = .006), and FTCD scores (F[2, 497] = 3.16, p = .044) differed by latent class. Pairwise comparisons showed that the substance use risk group had a higher proportion of males (62.3%) than the low risk (41.0%, χ^2 = 8.52, p = .004) and metabolic risk (43.0%, χ^2 = 8.36, p = .004) groups. Pairwise comparisons also showed that the metabolic risk group had a higher proportion of daily smokers (89.2%) compared to the substance use risk group (77.1%, χ^2 = 7.09, p = .008) and smoked significantly more cigarettes per day (M = 11.8, SD = 7.1) than the substance use risk group (M = 9.0, SD = 5.8, p = .005).

Readiness to Change Behaviors Characteristic of Each Latent Class

We also examined baseline readiness to change metabolic risk behaviors and substance use risk behaviors. On average, 31.2% of participants at risk were ready to change metabolic risk behaviors (SD = 7.7%), while only

Table 2. Proportion of young adults reporting readiness to change among those at risk for 10 health risk behaviors (%/N in preparation stage of change among those at risk)

	Baseline	3 months	6 months	12 months
Smoking	21.4% (107)	39.2% (132)	42.2% (121)	42.1% (125)
Unhealthy diet	23.8% (101)	24.4% (70)	22.0% (56)	27.9% (74)
Poor sleep habits	24.9% (89)	32.3% (70)	31.1% (61)	39.6% (84)
Low fruit and vegetable intake	28.5% (99)	30.9% (71)	31.7% (66)	40.1% (79)
Physical inactivity	38.3% (97)	38.0% (62)	32.7% (48)	45.0% (63)
Cannabis use	9.1% (23)	7.0% (12)	6.2% (9)	7.1% (12)
Poor stress management	40.3% (85)	37.5% (57)	38.3% (51)	40.9% (61)
Heavy alcohol use	14.2% (22)	12.2% (12)	10.0% (9)	15.9% (14)
Condomless sex	14.9% (14)	22.4% (17)	19.4% (13)	25.0% (19)
Other drug use	12.9% (9)	8.3% (4)	12.2% (5)	13.6% (6)

Response rates for health risk behavior measures were 100% (N = 500) at baseline, 70.8% (N = 354) at 3 months, 64.6% (N = 323) at 6 months, and 68.6% (N = 343) at 12 months. Proportions of participants in preparation were calculated among those who were at risk for each behavior.

Table 3. Latent class analysis of health risk behaviors at baseline and 3, 6, and 12 months, indices of model fit 1-class–6-class models

	Baseline (N = 500)						3 month follow-up (N = 354)					
	1-Class	2-Class	3-Class	4-Class	5-Class	6-Class	1-Class	2-Class	3-Class	4-Class	5-Class	6-Class
Number of free parameters	9	19	29	39	49	59	9	19	29	39	49	59
saBIC	3,414.65	3,358.13	3,344.61	3,351.72	3,360.81	3,374.06	3,836.89	3,732.83	3,704.68	3,714.99	3,725.46	3,737.54
AIC	3,409.20	3,346.62	3,327.04	3,328.09	3,331.12	3,338.32	3,830.62	3,719.59	3,684.47	3,687.81	3,691.31	3,696.42
BLRT	n/a	<0.0001	<0.0001	0.67	0.50	1.00	n/a	<0.0001	<0.0001	1.00	1.00	1.00
Entropy	n/a	.58	.70	.76	.66	.75	n/a	.77	.70	.75	.81	.93
	6 month (N = 323)						12 month (N = 343)					
	1-Class	2-Class	3-Class	4-Class	5-Class	6-Class	1-Class	2-Class	3-Class	4-Class	5-Class	6-Class
Number of free parameters	9	19	29	39	49	59	9	19	29	39	49	59
saBIC	3,502.38	3,387.40	3,380.12	3,380.16	3,382.82	3,391.29	3,733.40	3,597.03	3,577.31	3,562.42	3,571.50	3,581.63
AIC	3,496.93	3,375.89	3,362.55	3,356.53	3,353.13	3,355.55	3,727.41	3,584.38	3,558.01	3,536.47	3,538.89	3,542.37
BLRT	n/a	<0.0001	<0.0001	0.07	0.24	0.43	n/a	<0.0001	<0.0001	<0.0001	0.60	0.50
Entropy	n/a	.69	.59	.72	.83	.84	n/a	.66	.69	.67	.74	.83

AIC Akaike Information Criterion; *BLRT* Bootstrapped Likelihood Ratio Test; *saBIC* Sample Size Adjusted Bayesian Information Criterion.

12.1% of those at risk were ready to change substance use behaviors (*SD* = 2.7%). An independent samples *t*-test showed significantly greater readiness to change metabolic risk behaviors than substance use risk behaviors (t[6] = 4.06, p = .007).

Latent Transition Analysis

In three models, we examined the extent to which individuals in each HRB class at one time point were in the same class at the next time point using latent transition probabilities (Table 5). In all three models, the diagonals showed extremely high consistency, such that few participants transitioned between classes. Most transitions that did occur were between the metabolic risk and low risk classes, described as follows.

Baseline to Treatment End (3 months)

A transitional model with a 3-class/3-class solution showed good model fit (62 free parameters; saBIC = 7,126.68; AIC = 7,083.48; entropy = .88). Nineteen participants transitioned from low-risk to metabolic risk, while seven transitioned from metabolic to low. One participant transitioned from substance use risk to low risk.

Treatment end to 6 month follow-up

A second transitional model with a 3-class/3-class solution showed good model fit (62 free parameters; saBIC = 5,914.64; AIC = 5,882.88; entropy = .88). Seven participants transitioned from low-risk to metabolic risk, while five transitioned from metabolic to low. Two transitioned from substance use risk to low risk.

Six month follow-up to 12 month follow-up

A third transitional model with a 3-class/3-class solution showed good model fit (62 free parameters; saBIC = 5,842.58; AIC = 5,812.30; entropy = .83). Eleven participants transitioned from metabolic risk to low risk, while six transitioned in the opposite direction. Additionally, six participants transitioned from substance use risk to low risk and three transitioned from low risk to substance use risk.

Discussion

In our sample of young adult smokers, nearly all reported engaging in at least one other HRB at baseline and follow-up, the most prevalent at each time point being diet related. The most prominent patterns of HRBs at four time points highlighted that the more prevalent targets, in addition to tobacco, for behavioral

Table 4. Average latent class probabilities by class at baseline and 3, 6, and 12 month follow-ups

	Baseline (N = 500)			3 month follow-up (N = 354)		
	Substance	Metabolic	Low	Substance	Metabolic	Low
Substance	.826	.108	.066	.828	.082	.090
Metabolic	.022	.861	.117	.133	.848	.019
Low	.015	.103	.882	.079	.003	.918
	6 month follow-up (N = 323)			**12 month follow-up (N = 343)**		
	Substance	Metabolic	Low	Substance	Metabolic	Low
Substance	.833	.103	.064	.797	.116	.087
Metabolic	.160	.750	.090	.060	.885	.055
Low	.070	.038	.892	.044	.089	.867

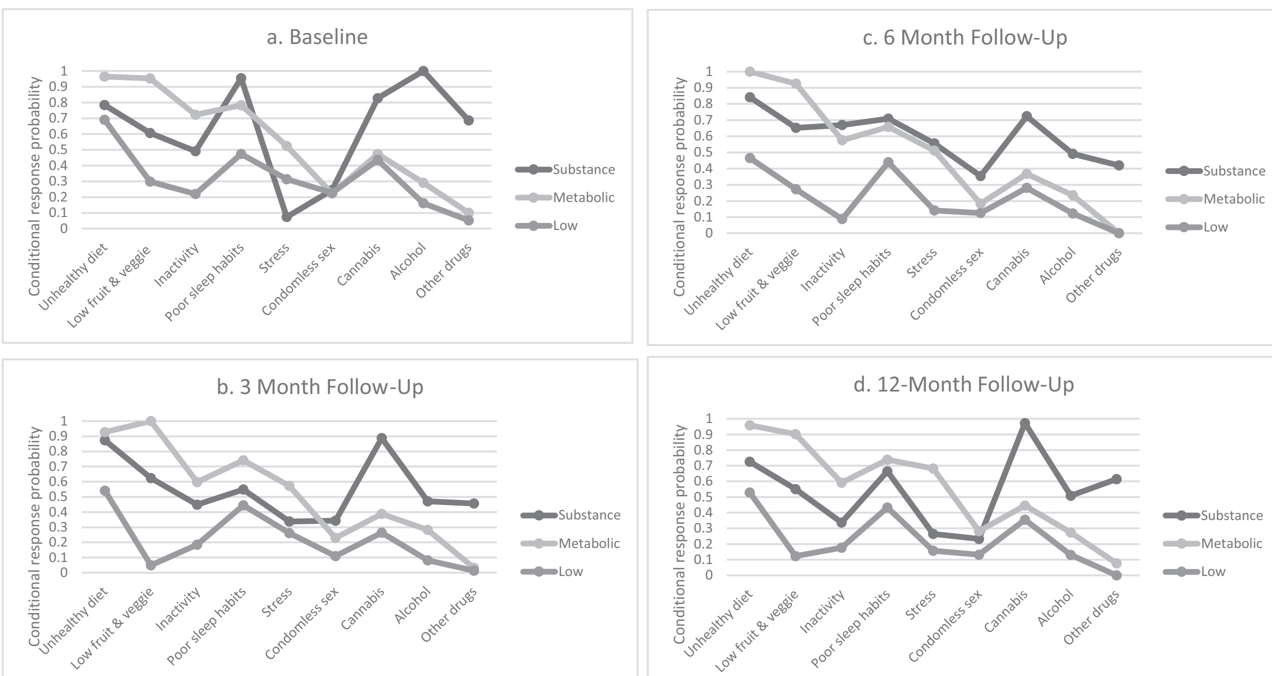

Fig. 2. Conditional response probabilities for the 3-class models at each time point.

change in young adult smokers are diet-inactivity, sleep habits, and cannabis use. The 3-class solution that fit the data best at all time points was similar to that found in a sample of adult smokers in a mental health treatment setting [41], with profiles for a global high-risk group, consisting of substance use and metabolic risks, and one in which risks were primarily metabolic (inactivity, unhealthy diet, sleep problems, and poor stress management). Three very similar profiles emerged in two very different samples of smokers (i.e., adults with serious mental illness recruited from inpatient psychiatry units, young adults recruited through social media), suggesting that metabolic and substance use patterns ought to be assessed and ideally addressed through direct treatment or referral, in the context of smoking cessation interventions. HRB patterns in young adult smokers may differ from those of the general young adult population.

Prior research in the general young adult population has found that smoking generally clusters with substance use and sexual risk behavior [28]. In the present study, wherein all participants were smokers, likelihood of engaging in condomless sex did not systematically vary with other HRBs. Employing broader measures of sexual risk behavior may have yielded an association between

Table 5. Latent transition probabilities for 3-class/3-class solution between baseline and 3 (Model 1), 3–6 (Model 2), and 6–12 month (Model 3) follow ups

	Baseline–3 month (N = 354)			3–6 month (N = 294)			6–12 month (N = 287)		
Time 1 class/ Time 2 class	Substance use	Metabolic	Low risk	Substance use	Metabolic	Low risk	Substance use	Metabolic	Low risk
Substance use	.989	.000	.011	.983	.000	.017	.919	.000	.081
Metabolic	.000	.928	.072	.000	.924	.076	.000	.868	.132
Low risk	.000	.238	.762	.000	.095	.905	.043	.095	.862

sexual risk behavior and substance use. However, given the similarities in HRB profiles between the present sample and adult smokers with serious mental illness [41], it is also plausible that the HRB profiles of young adults who smoke differ from those of the general young adult population. Research encompassing broader definitions of sexual risk behavior would be informative.

There were notable differences in stages of change for different HRBs that could be informative when adding health-related content to smoking cessation interventions for young adults. Given that overall, participants were most ready to change their diet, stress management, sleep, or physical activity, an intervention targeting the *metabolic* risk group would likely be well-received. Membership in the metabolic risk group at baseline was associated with a greater likelihood of smoking daily and with smoking more cigarettes per day. Young adult smokers with metabolic risk factors may be a group that would particularly benefit from cessation medications.

In contrast, motivation to change alcohol and drug use was generally low, suggesting that an intervention targeting the *substance use* group may need to especially focus on motivational enhancement. Cannabis use was common among participants in the *substance use* group, and those at risk for cannabis use were least ready to change this behavior compared to all other behaviors. Heavy alcohol use declined from baseline to follow-ups, while cannabis use remained elevated. Given previous reported differences in stages of change for tobacco and other substance use among young adults [67], smokers of all types may be less receptive to interventions targeting other substance use (especially cannabis) than they are tobacco or other HRBs. The substance use group had a higher proportion of males, suggesting that interventions with young adult male smokers may benefit from a focus on enhancing motivation to change substance use. Although class membership was mostly stable over the course of one year, transitions from low risk to metabolic risk were somewhat more frequent than transitions to substance use risk. This finding may reflect a general decline in substance use throughout one's 20s [68] and underscores the need for intervention on metabolic risk behaviors among the general population of young adult smokers.

Given a significant difference in smoking abstinence between treatment and control groups at the 3 month follow-up in the clinical trial [43], we hypothesized that participants would be more likely to transition to classes characterized by lower risk if they had participated in the Facebook smoking cessation intervention compared to the control condition at each time point. Results showed that classes were very stable over time, with few participants transitioning between them. As such, the model could not be reliably fit when treatment condition was included. This reflects the notable stability of young adults' patterns of HRBs over 12 months, which may be due to the demanding nature of multiple HRB change and limits of cognitive capacity and self-control, coupled with relatively low readiness to change [35]. Results suggest extended intervention content enhancing motivation and supporting behavior change for a few HRBs is likely needed to create meaningful change in multiple HRBs among young adult smokers participating in any form of smoking cessation intervention.

This study recruited a relatively diverse sample of young adult smokers in the USA. Notably, more than one in four participants identified as a sexual or gender minority (SGM). This may have been due to the high prevalence of both smoking [69–71] and social media use [72] among SGM individuals. Moreover, 8.2% of millennials identify as SGM compared to 3.5% of those in Generation X [73]. In this sample, SGM and non-SGM young adults did not significantly differ in smoking cessation rates or other health behaviors, with the exception of physical activity, over time [74]. Nonetheless, clustering of HRBs may vary by other individual differences (e.g., race, ethnicity, age, education), and future research could examine differences in the clustering of HRBs (i.e., latent classes) by individual characteristics. Notably, we identified few differences in latent class membership by individual characteristics, suggesting that the HRB profiles in this study have broad applicability to young adult smokers.

Study limitations include that the data were self-reported and subject to recall bias. Due to empty cells when additional parameters were included, we were unable to include treatment condition as a covariate or incorporate stage of change into LCA and LTA models. Future research should incorporate these additional characteristics. The sample was neither randomly sampled nor representative, thereby limiting generalization of study findings; however, as an initial investigation, the volume of HRBs among young adult smokers appears high and the patterns stable over 12 months.

Conclusions

HRBs are common among young adult smokers and three main patterns of risk behaviors were identified in this sample with evidence of stability over a year's time. There is potential benefit from targeting multiple HRBs in the context of a single intervention. Most young adult smokers present with multiple HRBs and few report readiness to change multiple behaviors. Results of this study support tailoring interventions to stage of change and matching treatment targets to the HRB profiles with which young adults present. In particular, smoking cessation interventions that include content targeting motivation for reducing substance use and taking action to improve metabolic risk behaviors appear needed.

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Compliance with Ethical Standards

Authors' Statement of Conflict of Interest and Adherence to Ethical Standards Dr. D. E. Ramo has provided consultation to Carrot, Inc., which makes a tobacco cessation device. Dr. J. J. Prochaska has provided consultation to pharmaceutical and technology companies that make medications and other treatments for quitting smoking and has served as an expert witness in lawsuits against the tobacco companies. All other authors have no conflicts of interest to disclose.

Authors' Contributions All authors contributed to and have approved the final manuscript.

Ethical Approval All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed Consent Informed consent was obtained from all individual participants included in the study.

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