Title
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Journal
Nicotine & Tobacco Research, 25(6)

ISSN
1462-2203

Authors
Stone, Matthew D
Braymiller, Jessica L
Strong, David R
et al.

Publication Date
2023-05-22

DOI
10.1093/ntr/ntad017

Peer reviewed

Nicotine and Tobacco Research, 2023, **25**, 1116–1124
https://doi.org/10.1093/ntr/ntad017
Advance access publication 31 January 2023
Original Investigation

Differentiating Reasons for Young Adult E-cigarette Use Using Maximum Difference Choice Models

Matthew D. Stone PhD[1,2], **Jessica L. Braymiller PhD[3]**, **David R. Strong PhD[1,2]**, **Sam N. Cwalina PhD[4,5]**, **Claudiu V. Dimofte PhD[6]**, **Jessica L. Barrington-Trimis PhD[4,5]**

[1]Herbert Wertheim School of Public Health and Human Longevity Science, University of California, San Diego, USA
[2]Moores UC San Diego Cancer Center, University of California, San Diego, USA
[3]Department of Community Health and Health Behavior, University at Buffalo, The State University of New York, New York, USA
[4]Department of Population and Public Health Sciences, Keck School of Medicine, University of Southern California, Los Angeles, USA
[5]USC Institute for Addiction Science, Los Angeles, USA
[6]Department of Marketing, Fowler College of Business, San Diego State University, San Diego, USA

Corresponding Author: Matthew D. Stone, PhD, Division of Health Policy, Herbert Wertheim School of Public Health and Human Longevity Science, University of California, San Diego, 3855 Health Sciences Drive, La Jolla, CA 92093-0901, USA. Telephone: (844) 534-2272; Email: m3stone@health.ucsd.edu

Abstract

Introduction: Understanding the reasons young adults use e-cigarettes (ie, vape)—and whether these motivations vary across groups—is essential for informing tobacco regulatory efforts.

Aims and Methods: An online panel of young adults who vape (n = 230; age = 18–30 years) completed a maximum difference discrete choice task for 15 reasons for vaping. Over 9 choice sets, participants were presented a subset of 5 reasons and selected the most and least important. Hierarchical bayesian analysis estimated the relative importance of each reason. Latent class analysis (LCA) identified groups with similarly ranked reasons for use. Multinomial regression evaluated the association between sample characteristics and class membership.

Results: Overall, relaxation had the highest probability of being the most important reason for use (14.8%), followed by harm reduction (13.2%), and flavors (10.3%). LCA identified five distinct classes, based on top reasons for use: 1. cessation (cigarette cessation [20.2%]; n = 80); 2. dependence (relaxation [20.5%] and unable to quit [19.2%]; n = 21); 3. relaxation (relaxation [20.6%]; n = 66); 4. socializing (socializing [22.2%]; n = 27); and 5. variable (boredom [10.5%] and acceptability [10.2%]; n = 36). Participants who were older, smoked cigarettes, or vaped more frequently were more likely to belong to the cessation class while those who were younger or more e-cigarette dependent were more likely to belong to the dependence class.

Conclusions: Perceived reasons why young adults vape are highly heterogeneous and dependent on the type of user. Tobacco regulatory efforts targeting distinct types of vapers are needed to minimize the adverse public health impact of vaping without compromising appeal for smoking cessation.

Implications: E-cigarette use remains high among young adults, with flavors, cost, and harm reduction (vs. combustible cigarettes) among the mostly commonly reported reasons for use. Yet, little is known about how relatively important these reasons are to the individual. Leveraging a maximum difference task, young adults' reasons for use were evaluated on a common interval scale and groups sharing similar reasons identified. Smoking cessation, dependence, relaxation, socialization, and boredom were respectively the most important reasons for use among five classes of vapers. E-cigarette regulatory policies should consider the distinct reasons for use as to not compromise their appeal for smoking cessation.

Introduction

Despite age-related divergence in recent trends in the prevalence of vaping among young adults,[1] e-cigarettes remain the third most commonly used substance within all ages of young adults, behind alcohol and cannabis.[2] The public health impact of e-cigarette use in this population remains a challenge to fully define,[3] given the differential benefits of e-cigarettes to young adult never-tobacco users (among whom there is little benefit to using e-cigarettes) and young adults who smoke combustible cigarettes (among whom there is likely a benefit to using e-cigarettes should they discontinue use of cigarettes). Understanding the reasons why young adults use e-cigarettes—and whether such reasons differ for different groups of individuals—may inform strategies to prevent never-smokers from initiating e-cigarette use while not discouraging individuals from transitioning away from cigarettes to e-cigarettes. Understanding reasons for use may elucidate which characteristics motivate different types of e-cigarette users, which in turn can inform regulatory strategies to reduce the adverse public health impact of e-cigarettes (eg, by targeting characteristics that are less important to established cigarette smokers seeking to switch to e-cigarettes).

Previous work has found that, among current e-cigarette users, reasons for use include smoking cessation and harm reduction,[4] but extend to include alleviation of craving or withdrawal symptoms, evasion of smoke-free policies, affordability, curiosity, social motivations, enticing flavorings, and pleasant aromatic smells.[5] Yet, much of our existing knowledge on the

Received: April 14, 2022. Revised: December 12, 2022. Accepted: January 30 2023.

reasons for using e-cigarettes has been limited to self-report items using "select all that apply" style measures which provide useful metrics on the proportion of a population that endorses a given reason but lack the capability to distinguish the importance of each reason. Ranking reasons allows for between and within group comparisons, but since the unit difference in the ranks is assumed to be equal, the measurement suffers in its ability to distinguish the degree to which each item is more or less important than another. Likert-type questions that scale the reasons overcome the intra- and inter-item comparison limitations but may suffer from poor targeting, leading to floor and ceiling effects which limit the ability to distinguish which reasons are truly most important.

To address this gap in knowledge, we evaluated 15 reasons for e-cigarette use via a novel maximum difference scaling (MaxDiff) task[6,7] among an online sample of young adults who use e-cigarettes. This orthogonal discrete choice task asks vapers to select the most and least important reasons for using e-cigarettes from a subset of items drawn from a larger pool and repeats this process multiple times. Analyzing the choices that participants make allows for the estimation of the relative importance of each reason at the individual level on a common ratio scale.[7] Compared to traditional scales, MaxDiff has been found to efficiently discriminate among items, readily identify group differences, and benefit from forcing respondents to make trade-offs.[7] These trade-offs better mirror reality and may allow regulatory authorities to gain insight into young adults' perceptions for why they use e-cigarettes. Moreover, these choice-based tasks are seeing increasing application as a means to investigate the potential impact of tobacco control efforts more precisely.[8–11]

Given that existing evidence suggests that young adults have different preferences for different product characteristics,[10] it is important to understand if any patterns in preferences can be identified when assessing reasons for using e-cigarettes by type of user (ie, those who use e-cigarettes for cigarette cessation purposes vs. relaxation purposes).[12] The combination of MaxDiff and latent class analysis (LCA)[13–15] employed in the current study allowed us to explore which reasons were relatively more important, identify clusters of vapers with similar reasons for use, and determine which user characteristics were associated with distinct reasons for use. Based on previous literature,[16–19] a total of 15 non-overlapping reasons for e-cigarette use were selected for evaluation which included items thought to be important to consumers (eg, the appeal of product characteristics such as flavors, addictive properties, and use for cessation). Using an online panel of vapers, we characterized and explored patterns in the reasons why young adults vape and identified potential variation in these patterns across important subpopulations.

Methods

Study Design and Sample

Young adult e-cigarette users in the United States were recruited via the online research platform Prolific.[20] An existing pool of volunteers were prescreened and invited to complete a survey of e-cigarette use and product preferences with remuneration of $5.00. To be eligible, participants must have indicated (past year) on the Prolific platform that they were 18–30 years old, lived in the United States, and stated that they, "Regularly use both tobacco products and e-cigarettes", "Previously smoked tobacco products. Now only use e-cigarettes", or "Only ever used e-cigarettes regularly". Prescreened respondents meeting study eligibility were invited via email by Prolific to take part in the study. Eligible participants who provided Informed consent then completed online anonymous measures regarding their e-cigarette use, related cognitions, and sociodemographics. A MaxDiff task involving reasons for e-cigarette use was then administered. The study was approved by the University of Southern California's Institutional Review Board.

Measures

Reasons for Using E-Cigarettes

A MaxDiff scaling task was designed to evaluate the magnitude of importance and the rank ordering of 15 distinct reasons[16–19] for using e-cigarettes (Table 1). In the task, participants were presented nine different combinations of five reasons for using e-cigarettes. For each set of five reasons, participants were asked: "Please consider the following reasons why people commonly use e-cigarettes. Considering only these 5 reasons, which is the most important and which is the least important reason that you use e-cigarettes?" Each participant received a unique set of nine combinations (each containing five reasons) drawn from a pool of 300 partial profile design variants. Orthogonal design profiles were generated in Lighthouse Studio (version 9.8.1; Sawtooth Software, Provo, UT) to ensure that each reason was presented three times (one-way level balance), appeared equally often with each other reason (two-way level balance), and had varied presentation orders (positional balance).[21]

Sociodemographic Characteristics

Measures of sample characteristics included age, gender, race/ethnicity, and subjective financial situation.[22]

E-cigarette and Other Tobacco Product Use

Measures of e-cigarettes use included the frequency of past 30-day vaping and the type e-cigarette device used most frequently (pod-based [Juul, Suorin, or Puffbar] or other device type [box/squonk mod or vape pens]). E-cigarette dependence was assessed by averaging the 8 items comprising the E-cigarette Dependence Scale (EDS; range = 0–4; α = 0.93).[23] Data from the Prolific screener determined tobacco product use history (exclusive user ["Only ever used e-cigarettes regularly"], former smoker ["Previously smoked tobacco products. Now only use e-cigarettes"], and dual user ["Regularly use both tobacco products and e-cigarettes"]).

Statistical Analysis

A MaxDiff analysis was run using a multinomial logit Hierarchical Bayesian (HB) estimation in Lighthouse Studio.[24] Resulting HB coefficients represent the degree of importance for each reason for use relative to the least important reason for use. HB coefficients were transformed into probability scaled scores (summing to 100)[25] which reflect the likelihood that a reason was selected as "most important" while also allowing the relative magnitude to be directly assessed (eg, a score of 15 is three times as important as a score of 5).

Internal Consistency

A root likelihood (RLH) fit statistic (range 0–1) was calculated to characterize the consistency in the patterns of choice responses.[26] To discriminate between consistent and random responses, 2000 mock participants answering the MaxDiff

Table 1. Reasons for E-cigarette Use and MaxDiff Importance Scores Among Ever Vapers Aged 18–30 Years Old (n = 230)

Label	Reasons for E-cigarette use	Importance[1]	Times selected[2]	
			Most	Least
Relaxation	To relax or relieve tension	14.8 (14.0, 15.5)	343 (50%)	27 (4%)
Less harmful	They might be less harmful than other forms of tobacco, such as cigarettes	13.2 (12.5, 14.0)	295 (43%)	43 (6%)
Flavor	They are available in flavors that taste good, such as mint, candy, fruit, or chocolate	10.3 (9.6, 11.0)	206 (30%)	51 (7%)
Affordability	They are affordable	10.3 (9.6, 10.9)	191 (28%)	40 (6%)
Cessation	To try to quit using tobacco products, such as cigarettes	9.2 (8.2, 10.1)	219 (32%)	91 (13%)
No smell	They do not smell	7.3 (6.7, 7.9)	132 (19%)	77 (11%)
Acceptability	They are more acceptable to non-tobacco users	6.2 (5.6, 6.8)	116 (17%)	87 (13%)
Less restriction	They can be used in areas where other tobacco products, such as cigarettes are not allowed	5.8 (5.3, 6.4)	106 (15%)	93 (14%)
Socializing	I like socializing while using them	5.7 (4.8, 6.5)	119 (17%)	136 (20%)
Boredom	Boredom or nothing else to do	4.2 (3.5, 4.9)	89 (13%)	202 (29%)
Experimentation	To experiment—to see what they are like	4.2 (3.7, 4.8)	84 (12%)	132 (19%)
Dependence	I cannot quit using them	3.8 (3.2, 4.5)	65 (9%)	201 (29%)
Vape tricks	I like to make vape clouds, do vape tricks, or participate in vaping competitions	2.2 (1.7, 2.7)	51 (7%)	322 (47%)
Peer or family use	Friends or family members use them	2.1 (1.7, 2.5)	38 (6%)	195 (28%)
Advertising	The advertising for them appeals to me	0.7 (0.5, 0.9)	16 (2%)	373 (54%)

Data expressed as Mean (95% Confidence Interval).
[1]From a multinomial logit Hierarchical Bayesian (HB) estimation. Importance scores are probability scaled, sum to 100, and reflect the relative likelihood that a given item is the most important reason for e-cigarette use.
[2]Sum of the times each reason was selected as the best and worst option and the proportion of time the reason was selected relative to the times it was shown (n = 690).

task randomly were simulated to ascertain a RHL cutoff value at the 95th percentile (0.269 RLH). Since random responses can bias preference estimates,[26] participants with RLH values below the cutoff were considered to have responded randomly and excluded (see results for details).

Latent Class Analysis

We performed a LCA in Lighthouse Studio on the 15-item scores generated from the MaxDiff to identify homogenous subgroups of young adults with similar reasons for using e-cigarettes.[13,27,28] To identify the optimal number of classes, we evaluated 6 latent class solutions and replicated each solution 100 times with random starting values. We determined the optimal number of classes[29–31] by evaluating the Consistent Akaike Information Criterion (CAIC), as it is one of the most widely used indices for determining class size for choice-based tasks,[32] the Bayesian Information Criterion (BIC) as it is considered to be the most reliable fit statistic that performs well in smaller samples, and interpretability of cluster response paatterns.[30] We sought a solution that was of sufficient size to suggest a meaningful base rate in the sample, that was theoretically meaningful, and maximized model fit.[29–31] Posterior probabilities assigned participants to their most likely class.

Univariate associations between sample characteristics and latent classes were explored using R[33] (version 4.0.0) and the "psych" package.[34] A set of full factorial multinomial logistic regressions were fit in the "nnet" package[35] to explore multivariable associations between sample characteristics and latent classes. To better understand these associations, we derived predicted probabilities of being in a given class for each level of each characteristic from the multinomial logit using the "effects" package.

Results

Study Population

A total of 297 young adults who had vaped in their lifetime completed the MaxDiff task. Among these, 42 participants did not report vaping in the past 30-days and were excluded from the analysis. HB analysis identified 25 participants with MaxDiff response patterns no better than chance (RLH ≤ 0.269), leaving 230 in the final analytic sample. Of these, 88 (38%) were female with a mean age of 25.1 years (SD = 3.6). Over half of the sample was non-Hispanic white (n = 127, 55%), and over two thirds had an income that met their basic needs (n = 155, 67%). Patterns of e-cigarette and cigarette use were roughly split with 36% (n = 82) using both products, 33% (n = 76) using only e-cigarettes but previously using cigarettes, and 31% (n = 72) only ever using e-cigarettes. Participants vaped an average of 17 days in the past month (SD = 11.3) mostly from pod-based products (n = 142, 62%). Overall, the sample was fairly low in e-cigarette dependence (mean = 1.4, SD = 1.0).

Maximum Difference Choice Models

Across the entire sample, relaxation and tension relief had the highest probability of being the most important reason for using e-cigarettes (14.8% [95% CI = 14.0%, 15.5%]), followed by lower harm perception (13.2% [95% CI = 12.5%, 14.0%]), flavor (10.3% [95% CI = 9.6%, 11.0%]), affordability (10.3% [95% CI = 9.6%, 10.9%]), and cigarette cessation (9.2% [95% CI = 8.2%, 10.1%]). The least important reasons for use included peer or family use (2.1% [95% CI = 1.7%, 2.5%]) and advertising (0.7% [95% CI = 0.5%, 0.9%]; Table 1).

Latent Class Analysis (LCA)

Starting with a single class solution, both CAIC and BIC indices decreased substantially with each additional class until they were minimized, and an optimal 5-class solution was identified (Supplementary eTable 1). Results of the LCA revealed that the more parsimonious 4-class solution was largely a restricted version of the 5-class solution which contained an additional theoretically important group (ie, primary reason included socializing; Supplementary eFigure 1). Thus, we determined the 5-class solution to best fit the data as the CAIC and BIC values were smallest for this solution[30,31,36] while also yielding meaningful and interpretable subgroups,[29,31] each comprising >8% of the sample.[30,31,37] Results from the LCA (Figure 1 and Supplementary eTable 2) identified five distinct groups of young adults who vape based on highest ranked reasons for use: (1) a cessation class (n = 80) with key reasons that included cigarette cessation (20.2%), harm reduction (17.9%), and relaxation (13.3%); (2) a dependence class (n = 21) whose chief reasons for use included relaxation (20.5%), being unable to quit (19.2%), and harm reduction (14.2%); (3) a relaxation class (n = 66) whose top reasons included relaxation (20.6%), affordability (14.7%), and flavors (13.9%); (4) a socializing class (n = 27) with key reasons that included socializing (22.2%), flavors (12.3%), and relaxation (11.7%); and lastly (5) a variable class (n = 44) whose primary reasons for use included boredom (10.5%), acceptability (10.2%), and no smell (9.1%).

Associations with Class Membership

Differences in sample characteristics with 95%CIs for trends by latent class membership are presented in Table 2. On average, those in the cessation class were older (26.6 years old) while those in the dependence class tended to be younger (22.4 years old) than those in the remaining classes who were roughly the same age (24.0–24.9 years old). Use of pod-based e-cigarettes was highest for the dependence class (81%) and lowest for the cessation class (52%). On average, more frequent past 30-day vaping was reported among those in the cessation (21.3 days) and dependence (19.3 days) classes than those in the relaxation (13.9 days) and variable (12.2 days) classes. Those in the dependence class tended to have heightened dependence score (EDS mean = 2.0) relative to those in the other four classes (EDS range: 1.1–1.5). One average, the pattern of MaxDiff response were less consistent among those the variable class than all other classes (RLH's = 0.42 versus 0.47–0.58).

Omnibus f-tests from multinomial logit models demonstrated that age, frequency of vaping, e-cigarette dependence, and patterns of tobacco use were each independently associated with class membership (Table 3 and Supplementary eTable3). Those who reported current dual use of e-cigarettes and cigarettes were 68–82% less likely to belong to the dependence (OR = 0.18 [95% CI = 0.04, 0.89]), relaxation (OR = 0.32 [95% CI = 0.11, 0.92]), or socializing (OR = 0.26 [95% CI = 0.07, 0.94]) classes as compared to the cessation class. Similarly, those who reported previous cigarette use were 79–90% less likely to belong to the relaxation (OR = 0.21 [95% CI = 0.07, 0.62]) or socializing (OR = 0.10 [95% CI = 0.02, 0.44]) classes than the cessation class. Greater e-cigarette dependence was associated with higher odds of classification in the dependence class versus cessation class (OR = 2.84 [95% CI = 1.43, 5.62]). Increased use of e-cigarettes was associated with reduced odds of belonging to relaxation (OR = 0.94 [95% CI = 0.91, 0.98]) and variable (OR = 0.92 [95% CI = 0.87, 0.96]) classes compared to the cessation class. Relative to the cessation class, participants were 28% less likely to belong to the dependence class (OR = 0.72 [95% CI = 0.59, 0.87]) and 16% less likely to belong to the variable class (OR = 0.84 [95% CI = 0.73, 0.98]) as age increased.

Figure 2 depicts how differences in age, frequency of use, dependence, and other tobacco use related to shifts in the probabilities of class membership. Holding all other variables in the model constant, as age increased, the probability of belonging to the cessation class increased while the probability of belonging to the dependence and variable classes decreased. The probability of belonging to the cessation class was highest for former smokers while exclusive e-cigarette users had the highest probability of belonging to the relaxation class. Dual users had equally high probabilities of belonging to either the relaxation class or cessation class. Greater e-cigarette dependence was observed in the dependence class relative to all other classes, such that the probability of belonging to this class was over 40% at the highest level of EDS. Lastly, the frequency of past 30-day e-cigarette use was greater among vapers in the cessation class and lowest for the variable class. The probability of belonging to the cessation class increased as vapers approached daily use of e-cigarettes.

Discussion

The most important reasons for using e-cigarettes among young adults who vape included relaxation/tension relief, as well as perceptions of harm reduction which were found to be nearly 50% more important than the next three ranked reasons (eg, flavorings, product affordability, and smoking cessation). However, reasons for using e-cigarettes varied across individuals and we identified five classes of vapers that shared similar reasons for using e-cigarettes: (1) a cessation class whose reasons centered around harm reduction and using the product for relaxation and to quit smoking, (2) a dependence class who also preferred e-cigarettes' relaxation properties but were unable to quit using them, (3) a relaxation class who preferred the relaxing properties, flavorings, and affordability of e-cigarettes, (4) a socializing class who like the flavorings and to use the product while socializing, and (5) a variable class who did not have strong reasons for use but used e-cigarettes for their acceptability and to relieve boredom. Additionally, we found that users who were older, smoked cigarettes, or vaped more frequently in the past month were more likely to belong to the cessation class. Conversely, those who were younger or reported higher levels of e-cigarette dependence were more likely to belong to the dependence class.

When considering e-cigarette product regulations, the US Food and Drug Administration seeks to strike a balance between reducing the appeal of e-cigarettes to those who have never used any nicotine products, while not discouraging current cigarette users from switching to a potentially less harmful product.[3,38] Data from this study support restriction

Figure 1. Probability Scaled Importance Scores for E-cigarette Use Reasons across Latent Classes (n = 230). Probability scaled importance scores (range 0–100) reflect the relative likelihood that a given reason is the most important reason for e-cigarette use. Superscripts denote the relative rank within class. Reasons in the x-axis ordered by overall importance in the total sample.

on flavors in vaporized tobacco products, which were more important to those using the product for relaxation or socialization than to those using e-cigarettes for smoking cessation.[39] Importantly, existing research suggests that appealing flavors in e-cigarettes contribute to youth initiation.[40–42] Indeed, our findings support this claim as flavors

Table 2. Sample Characteristics and Univariate Associations with Latent Class Reasons for E-cigarette Use (*n* = 230)

Characteristic	Reasons for E-cigarette use latent classes[1]					*p*-value[2]
	n = 80	*n* = 21	*n* = 66	*n* = 27	*n* = 36	
	Cessation	Dependence	Relaxation	Socializing	Variable	
Age	26.6 (26.3, 26.9)	22.4 (21.8, 23.1)	24.9 (24.4, 25.4)	24.5 (23.9, 25.1)	24.0 (23.4, 24.6)	<.001
Gender						.12
Female	37 (46%)	10 (48%)	24 (36%)	9 (33%)	8 (22%)	
Male	43 (54%)	11 (52%)	42 (64%)	18 (67%)	28 (78%)	
Race/Ethnicity						.16
White	49 (61%)	15 (71%)	34 (52%)	14 (52%)	15 (42%)	
Non-white	31 (39%)	6 (29%)	32 (48%)	13 (48%)	21 (58%)	
Income						.17
Live comfortably	13 (16%)	7 (33%)	22 (33%)	6 (22%)	12 (33%)	
Meet needs	33 (41%)	7 (33%)	25 (38%)	15 (56%)	15 (42%)	
Basic expenses	34 (42%)	7 (33%)	19 (29%)	6 (22%)	9 (25%)	
Tobacco product use						<.001
Exclusive e-cig	9 (11%)	11 (52%)	27 (41%)	13 (48%)	12 (33%)	
Former smoker	40 (50%)	6 (29%)	15 (23%)	4 (15%)	11 (31%)	
Dual user	31 (39%)	4 (19%)	24 (36%)	10 (37%)	13 (36%)	
Device type						.16
Pod-based device	42 (52%)	17 (81%)	42 (64%)	18 (67%)	23 (64%)	
Other device types	38 (48%)	4 (19%)	24 (36%)	9 (33%)	13 (36%)	
Dependence	1.5 (1.4, 1.6)	2.0 (1.8, 2.2)	1.1 (1.0, 1.2)	1.4 (1.1, 1.6)	1.2 (1.0, 1.4)	.004
30-day frequency	21.3 (20.1, 22.4)	19.3 (16.5, 22.1)	13.9 (12.6, 15.2)	16.3 (14.2, 18.4)	12.2 (10.3, 14.1)	<.001
Choice consistency[3]	0.58 (0.56, 0.60)	0.57 (0.53, 0.62)	0.53 (0.50, 0.55)	0.47 (0.43, 0.51)	0.42 (0.38, 0.45)	<.001

[1]Data presented as mean (95% confidence interval) or *n* (%).
[2]Univariate differences from One-way ANOVA; chi-square test of independence.
[3]RLH (Root Likelihood) fit statistic from multinomial logit Hierarchical Bayesian estimation. Higher values represent more consistently in the answers to the MaxDiff choice questions.

Table 3. Association of Sample Characteristics with Latent Classes of Reasons for E-cigarette Use (*n* = 230)

Regressor[1]	Cessation class versus				Omnibus *p*-value[2]
	Dependence class	Relaxation class	Socializing class	Variable class	
Age	0.72 (0.59, 0.87)[a]	0.94 (0.83, 1.06)[b]	0.91 (0.78, 1.07)[b]	0.84 (0.73, 0.98)[a,b]	.004
Gender					.11
Female	Ref	Ref	Ref	Ref	
Male	1.28 (0.42, 3.92)[a]	1.75 (0.82, 3.72)[a]	2.02 (0.75, 5.46)[a]	3.58 (1.33, 9.59) [a]	
Race/Ethnicity					.18
White	Ref	Ref	Ref	Ref	
Non-white	0.64 (0.20, 2.08)[a]	1.57 (0.76, 3.28)[a,b]	1.48 (0.57, 3.83)[a,b]	2.38 (0.97, 5.83)[b]	
Income					
Live comfortably	Ref	Ref	Ref	Ref	.30
Meet needs	0.34 (0.08, 1.40)[a]	0.38 (0.14, 0.99)[a]	0.96 (0.28, 3.29)[a]	0.44 (0.14, 1.35)[a]	
Basic expenses	0.44 (0.11, 1.84)[a]	0.36 (0.13, 0.95)[a]	0.45 (0.11, 1.79)[a]	0.30 (0.09, 1.02)[a]	
Tobacco product use					.042
Exclusive e-cig	Ref	Ref	Ref	Ref	
Former smoker	0.23 (0.05, 1.03)[a]	0.21 (0.07, 0.62)[a]	0.10 (0.02, 0.44)[a]	0.47 (0.13, 1.71)[a]	
Dual user	0.18 (0.04, 0.89)[a]	0.32 (0.11, 0.92)[a]	0.26 (0.07, 0.94)[a]	0.50 (0.14, 1.81)[a]	
Device type					.85
Pod-based device	Ref	Ref	Ref	Ref	
Other device types	0.75 (0.20, 2.84)[a]	1.14 (0.52, 2.48)[a]	1.12 (0.40, 3.15)[a]	1.58 (0.60, 4.17)[a]	
E-cigarette dependence	2.84 (1.43, 5.62)[a]	1.02 (0.66, 1.58)[b]	1.34 (0.77, 2.33)[a,b]	1.45 (0.86, 2.46)[a,b]	.018
30-day frequency	0.96 (0.90, 1.02)[a]	0.94 (0.91, 0.98)[a]	0.96 (0.92, 1.01)[a]	0.92 (0.87, 0.96)[a]	.004

Data expressed as Odds Ratios (95% Confidence Interval). From a multinomial logistic regression predicting latent classes from covariates with the cessation class serving as the referent group.
[1]Superscript letters denote tests of independence of effect estimates across each row; estimates sharing letters are not statistically significantly different from one another ($p < .05$).
[2]From separate drop-in-deviance tests comparing the residual deviances in the fully adjusted model to a series of reduced models each omitting a single examined regressor.

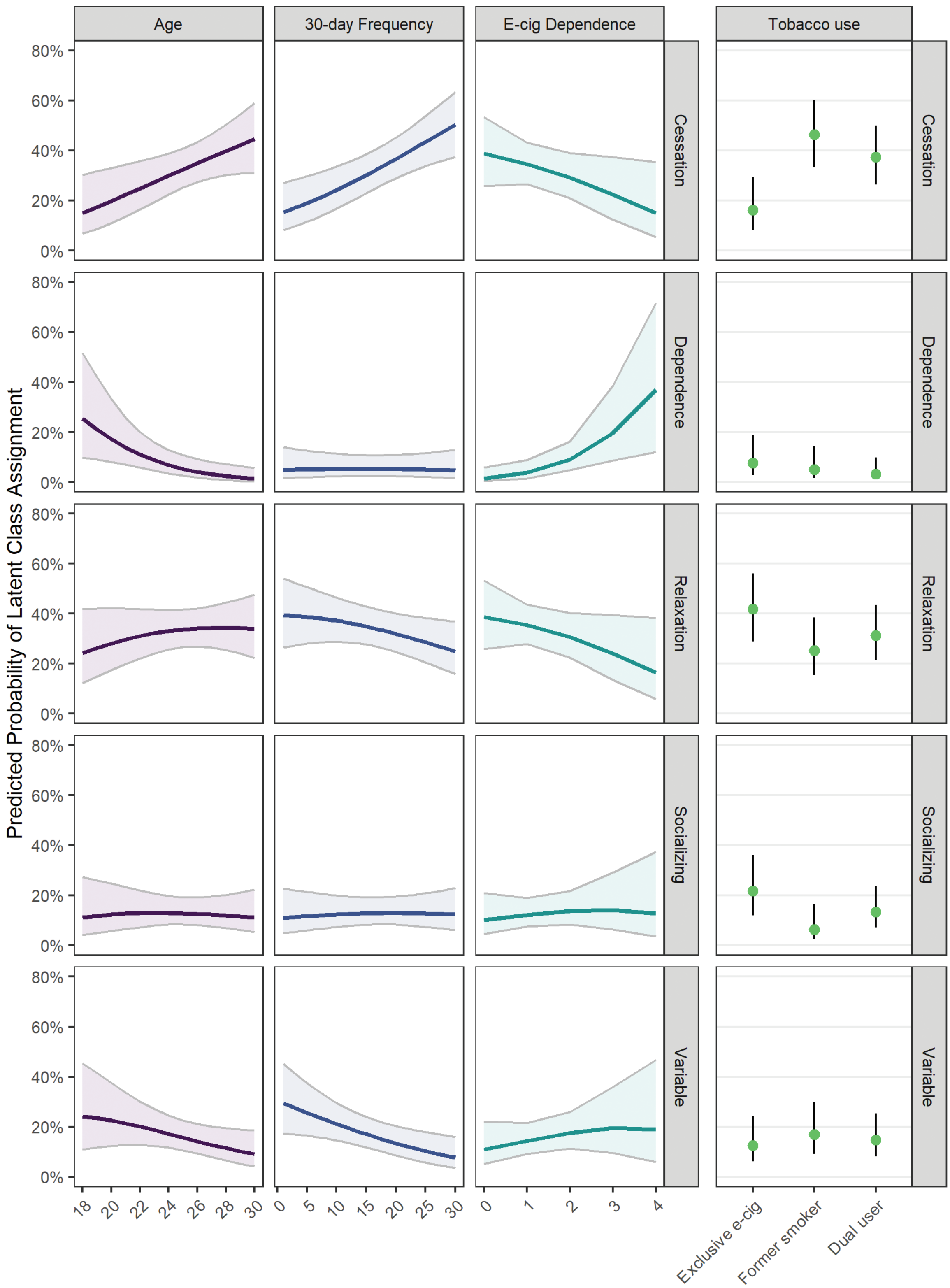

Figure 2. Predicted Probabilities and 95% Confidence Intervals for Latent Class Reasons for E-Cigarette Use by Sample Characteristics (n = 230)

were the third most important reason for use overall, second for the socializing class, and third for the relaxation class. Moreover, the dependence class was characterized mostly by younger ages where flavors was the fourth most important reason for vaping (behind dependence, relaxation, and harm reduction). Yet, among this class, the importance of flavors (9.1%) was only half of that associated with being unable to quit (19.2%) or using the product to relax or relieve stress (20.5%).

Reasons for vaping were more diffuse among participants assigned to the variable class than among vapers in other classes, where importance scores were discernably different.

This was supported as the pattern of responses in the MaxDiff task was also less consistent in this group. While boredom and acceptability were among the top reasons for use among this group, these reasons may not define this class any more than some of the other reasons examined (eg, experimentation or vape tricks). This class also tended to use e-cigarettes less frequently reflecting that they may not have clearly developed reasons for use. Future research is needed to understand this population.

The largest class of vapers was characterized by motivations for cessation. We found that older individuals, former and current smokers, and those who more frequently vaped were more likely to be assigned to the cessation class. Among this group, the most important reason for use was "to try to quit tobacco products, such as cigarettes" followed by the perception that the products "might be less harmful than other forms of tobacco"; these two reasons were nearly three times as important as the products being "available in flavors that taste good". However, the affordability and acceptability of the products was ranked similarly to flavor, suggesting that flavor contributes meaningfully to motivating one to continue vaping among those trying to quit smoking.[42]

Our findings are consistent with previous literature on reasons for e-cigarette use.[5,18,43] A significant limitation to previous work, however, is the inability to delineate *how important* each reason is to the individual e-cigarette user (relative to other reasons). For instance, it is plausible that one of the most commonly endorsed reasons for using e-cigarettes (eg, "They do not smell") holds less weight (ranked 6th in the current study) among the plethora of reasons for why an individual might use a product. Thus, what is commonly reported (ie, salience) may not be what is perceived to be important (ie, weight) among those who vape. This study examined reasons for use using a relative difference framework thus allowing us to examine both the between and within subject importance associated with each reason. Ultimately, MaxDiff is an improved measurement approach given the intra- and inter-item comparison of the reasons for e-cigarette use on a common ratio scale.[7]

The study had the following limitations: we used a relatively small convenience sample recruited through the online research platform Prolific, thus limiting the study's generalizability. In addition, data on combustible tobacco product use was not collected as part of the main study questionnaire; we instead relied on prescreening questions that may be have been self-reported up to 1 year prior to study enrollment, possibly contributing to classification bias. Further, while relaxation was the primary reason for use, it is possible that this is merely a post-hoc rationalization in the form of social desirability bias or self-deception to justify the use of a harmful product. Despite our effort to select common reasons for using e-cigarettes, participants were not given an option to select "none of the above" in the MaxDiff task and thus it is possible that none of the 15 reasons we identified were applicable to some of the vapers in our sample. Despite limitations, the study had multiple strengths. When determining the most important reasons for use, our study assessed the rewarding properties of e-cigarettes (eg, relaxation and tension relief), which many studies omit possibly due to the known rewarding effects from consuming nicotine. However, our approach allowed us to scale reasons in such a way that we could directly compare the importance of various reasons for use. Additionally, the MaxDiff task benefited from forcing respondents to make trade-offs between the reasons, thus enhancing external validity.

Conclusion

The most prominent reasons for vaping involved perceptions of relaxation and tension relief, comparative harms, flavors, and affordability, yet their relative importance differed by distinct classes of vapers. These data highlight the need for tobacco regulatory efforts that differentially target diverse populations of vapers in order to minimize the adverse public health impact of vaping among young people.

Supplementary Material

A Contributorship Form detailing each author's specific involvement with this content, as well as any supplementary data, are available online at https://academic.oup.com/ntr.

Funding

Research reported in this publication was supported by the National Cancer Institute (NCI) of the National Institutes of Health (NIH) and the US Food and Drug Administration (FDA) Center for Tobacco Products under Award Numbers U54CA180905 and U54CA229973 as well as by National Institute on Drug Abuse (NIDA) Award Number K01DA042950. The content is solely the responsibility of the authors and does not represent the official views of the NIH or the FDA.

Declaration of Interest

The authors have no potential conflicts of interest to disclose.

Data Availability Statement

Data are available upon reasonable request.

Ethics approval: Ethical approval for the study was granted by the Institutional Review Boards at the University of Southern California. All participants provided fully informed consent.

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