Patterns and Predictors of Smoking by Race and Medical Diagnosis During Hospital Admission: A Latent Class Analysis

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Abstract

Hospital-based tobacco treatment programs provide tobacco cessation for a diverse array of admitted patients. Person-centered approaches to classifying subgroups of individuals within large datasets are useful for evaluating the characteristics of the sample. This study categorized patients who received tobacco treatment while hospitalized and determined whether demographics and smoking-related health conditions were associated with group membership. Chart review data was obtained from 4854 patients admitted to a large hospital in South Carolina, USA, from July 2014 through December 2019 who completed a tobacco treatment visit. Smoking characteristics obtained from the visit interview were dichotomized, and then latent class analysis (LCA) was conducted to categorize patients based on smoking history and interest in stopping smoking. Finally, logistic regressions were used to evaluate demographics and smoking-related health conditions as predictors of class membership. LCA generated 5 classes of patients, differentiated by heaviness of smoking and motivation to quit. Patients who were black/African American were more likely to be lighter smokers compared to white patients. Hospitalized patients with a history of hypertension, diabetes, and congestive heart failure were more likely to be motivated to quit and also were more likely to be lighter smokers at the time of hospitalization. Hospitalized patients who smoke and receive tobacco treatment are heterogeneous in terms of their smoking histories and motivation to quit. Understanding latent categories of patients provides insight for tailoring interventions and potentially improving tobacco treatment outcomes.

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Introduction

Tobacco use is the leading cause of over 8 million preventable diseases and deaths worldwide and is a contributing factor to several leading causes of mortality, such as heart disease and cancer (Barua et al., 2018; Stanton et al., 2016). While 68% of people who smoke express interest in cessation (Babb et al., 2017), results have shown low rates of long-term abstinence from unassisted quit attempts (Hughes et al., 2013).

Hospitals have an opportunity to provide effective tobacco cessation support for admitted patients given the potential for increased motivation to quit and the smoke-free policies many hospitals have in place. "Opt-out" models, in which treatment is provided as standard procedure, may be especially suited for increasing motivation and access to cessation treatment for a variety of patients who may otherwise not have such resources (Nahhas et al., 2017; Richter & Ellerbeck, 2015). Studies have shown tobacco treatment programs (TTPs) incorporated into hospital and medical systems are an effective way to increase smoking cessation (Cartmell, Dooley, et al., 2018; Miller et al., 1997; Nahhas et al., 2017; Palmer et al., 2021; Rigotti et al., 2012; Stevens et al., 1993), leading to a reduction in morbidity and mortality rates for smoking comorbidities (Mohiuddin et al., 2007; Smith & Burgess, 2009; Van Spall et al., 2007). However, cessation rates remain lower than desired, and long-term abstinence is difficult to achieve. Therefore, understanding individual differences in patient presentations is critical to enhancing the efficacy of these interventions.

Hospital admissions require the provider to use time-efficient strategies to treat their patients. Given the acute nature of the hospital visit, time is limited for health prevention services, and thus, is a barrier to delivering individualized tobacco cessation services (Rojewski et al., 2019; Stack & Zillich, 2007). For this reason, strategies that can facilitate service delivery while maintaining personalized care are needed. One such method for achieving efficiency is to split patients into categories or groups based on clinically relevant characteristics. However, generation of patient groupings can be subjective, which can lead to bias in classification. A potentially less biased, person-centered approach, involves stratifying patients into groups using latent class analysis (LCA). LCA is a statistical modeling procedure that detects patterns among observed variables and assigns a class value based upon the likelihood each subgroup encompasses their characteristics (Ylioja et al., 2017). In a medical setting, utilization of an LCA algorithm allows for quick decision making by identifying subgroups of patients based on key patient characteristics (Lanza & Rhoades, 2013). Latent subgroups can also be analyzed in relation to one another to evaluate differences in representation of other related aspects, such as patient demographics or health conditions. This allows for future intervention development strategies to tailor treatments to latent subgroups to address their unique needs. LCA has been used to evaluate homogeneity in patterns of tobacco use (e.g., Sutfin et al., 2009) and associated correlates, such as dependence (e.g., Kypriotakis et al., 2018) and race and ethnicity (e.g., Choi et al., 2018).

The present study used LCA to identify latent patterns of smoking history and motivation to quit among a large sample of tobacco users who received a tobacco treatment bedside consult while hospitalized. Patient demographics and health conditions were examined in relationship to group membership to further distinguish identified subgroups.

Methods

Participants

The Tobacco Treatment Program (TTP) at the Medical University of South Carolina (MUSC) is a dedicated service that treats both inpatient and outpatient populations at four different hospitals within the system (Nahhas, Wilson, et al., 2017). Staff include psychologists, pharmacists, and counselors, who consist of pre-doctoral psychology interns and a certified Tobacco Treatment Specialist. Inpatient service is opt-out, meaning that all patients are approached for treatment and patients must actively decline services (Nahhas, Cummings, et al., 2017). In this program, counselors are alerted daily of all patients admitted to the hospital that report tobacco use. Counselors then visit patients in their rooms to complete an interview, provide brief counseling, and send medication orders to attending physicians if requested and accepted by the patient. Patients are then enrolled in an automated, interactive voice recognition (IVR) protocol, wherein patients are offered a referral to outpatient counseling or the South Carolina Quitline. This program has demonstrated clinical efficacy in improving treatment outcomes, reducing readmissions, and cutting costs (Cartmell, Dismuke, et al., 2018; Cartmell, Dooley, et al., 2018; Palmer et al., 2021).

Chart data were retrieved from patients who were admitted to the hospital between July 2014 and December 2019. Patients who reported cigarette smoking, agreed to the bedside intervention, and accepted enrollment into the IVR system were included in the present analysis. Of those identified, patient MRNs (medical record numbers) were used to obtain data on history of health conditions that are associated with cigarette smoking. This study was exempt from participant consent and approved by the MUSC Institutional Review Board. Due to the sensitive nature, the data are not shared publicly.

Measures

Medical chart data. Patients' age, race, and biological sex were obtained from the medical record. Data on history of health conditions were pulled from each patient's chart on the day of admission (i.e., "Problem List" via Epic electronic medical record system) for the following: hypertension, chronic obstructive pulmonary disease (COPD), diabetes, heart failure, stroke, and cancer. These conditions were chosen based on those most prevalent among people who smoke (Rojewski et al., 2016).

Smoking characteristics. TTP clinicians asked patients to report on how long they had been smoking (years), how often they smoked over the past month (daily or non-daily), how many cigarettes were smoked per day, how soon they smoked after waking, and if they lived with another person who smokes. These items were selected for use in the model based on previous literature that suggests higher dependence may be related to treatment receptivity and outcomes (Mussulman et al., 2019). Given the changing landscape of tobacco product use in the general population (Zhu et al., 2017) and among hospitalized patients (Rigotti et al., 2015), self-reported alternative tobacco product use (cigars, oral tobacco, or e-cigarettes) was collected for use in the model. Patients were also asked how many times, if any, they tried to quit smoking during the past year. Importance to quit was measured by asking "How important is quitting smoking to you on a scale of 1-5, with 5 being the most important?" Confidence in quitting was measured by asking "How confident are you that you will be able to remain smoke free on a scale of 1-5, with 5 being the most confident?" Motivational factors were included in the model as hospitalization may represent a "teachable moment" promoting health behavior change, such as smoking cessation (Dohnke et al., 2012). Finally, patients were asked if they had requested and received a quit smoking medication (such as NRT, or nicotine replacement therapy) during hospitalization. This variable is especially salient to the patient's physical dependence, motivation, and receptivity to treatment given the opt-out nature of the program (Rigotti et al., 1999).

Statistical Methods

All analyses were conducted on Mplus v8.1 and SAS 9.4. To begin, a median split was used to dichotomize years smoking, cigarettes per day, number of past-year quit attempts, importance of quitting, and confidence in quitting. Patients were categorized based on responses to smoking characteristics questions using LCA. This analysis assumes that covariation among variables measured is attributed to a single latent factor (Lanza et al., 2003; Lanza &

Rhoades, 2013). Preliminary models were run to produce two latent classes, and further iterations increased the number of classes. Next, model fit and class differentiation was interpreted (Nylund-Gibson & Choi, 2018). Fit statistics (Akaike information criterion [AIC], Bayesian information criterion [BIC], sample-size adjusted BIC [SSA-BIC]) were used to assess model fit and error, with lower values indicating better fit. Entropy was used to assess the degrees to which the classes were inherently distinct from one another, with increasing values implicating better class distinction. Bootstrapped likelihood ratio tests (BLRTs) compared the fit statistics of each model iteration with the prior (k-1) class iteration, with a significant difference between models indicating a better fit. Finally, models were subjectively interpreted for content of classes. Once parsimony in class interpretation decreased and BLRTs failed to show better fit ($p > .05$), the LCA iterations were terminated and the final model was selected.

Unadjusted logistic regressions were used to evaluate patient demographic characteristics (sex and race), and smoking-related health condition diagnosis as predictors of class membership.

Results

Patient Characteristics

Chart review identified 4,854 patients who reported current cigarette smoking upon admission and completed an interview with the TTP while inpatient. Patient demographics can be seen in Table 1. On average, participants were middle aged, male, and identifying as either white or black/African American. A majority of patients reported daily smoking, averaging about 15 cigarettes per day and a smoking history of approximately 27 years. Only 288 (5.9%) of patients reported current use of an alternative tobacco product, such as cigars, e-cigarettes, or oral tobacco.

Median splits dichotomized smoking characteristics into the following variables (affirmative or negative): high cigarettes per day (≥ 15 cigarettes per day), high smoking history (≥ 28 years smoking history), high dependence (smoke within first 5 minutes of waking), made past year quit attempt (≥ 1 quit attempt in the past year), high importance of quitting (≥ 4 on 1-5 scale), and high confidence in the ability to quit (≥ 4 on 1-5 scale). Daily smoking status, living with another person who smokes, use of any other tobacco products, and receipt of NRT remained dichotomized as affirmative or negative for the analysis. Medical diagnoses from the problem list were obtained from 4,516 (93.03%) patients. Those with missing data were coded as not having the diagnosis of interest.

Class Models

Six iterative models were run, and fit statistics can be seen in Supplemental Table 1. Model fit indices showed the data fit best into 5 latent classes, shown in Figure 1. Fit statistics for this model were as follows: AIC = 47451.46; BIC = 47801.79; SSA-BIC: 47630.198; entropy = 0.70. BLRTs showed that the 5-class model was a superior fit to the 4-class model ($p < .001$), but the 6-class model was not superior to the 5-class model ($p = .0197$).

In general, the probability of using an alternative product was very low across classes, and the probabilities of long-term smoking and of living with another person who smokes were moderate.

Table 1. *Patient Demographics and Smoking Characteristics*

Characteristic (N = 4854)	**M or N**	**SD or %**
Age	45.35	25.17
Sex		
Male	2647	54.5%
Female	2206	45.5%
Race/Ethnicity		
White	2628	62.3%
Black/African American	1480	35.1%
Hispanic	62	1.5%
American Indian/Alaska Native	22	< 1%
Asian	15	< 1%
Mixed/ Other	14	< 1%
Daily smoking	3906	80.5%
Cigarettes per day	15.9	11.26
Years smoking	27.9	15.59
Time to first cigarette		
< 5 minutes	2266	46.7%
6-30 minutes	531	10.9%
31-60 minutes	247	5.1%
> 61 minutes	434	8.9%

Unmotivated Heavy Smoking (UHS); n = 1396, 28.8%

The first class identified all reported daily smoking and showed high probabilities of reporting high dependence and heavy cigarette smoking. In addition, this group had low probabilities of attempting to quit in the past year, rating quitting as important, and reporting high confidence in their ability to quit. This group had a relatively high probability of receiving medications while hospitalized.

Motivated Heavy Smoking (MHS); n = 1381; 28.5%

The second class identified had all reported high dependence and also showed high probabilities of daily smoking and heavy cigarette smoking. This group also showed high probabilities of having a past year quit attempt, receiving medications in the hospital, and reporting high importance of and confidence in quitting.

Unmotivated Light Smoking (ULS); n = 688, 14.2%

In the Unmotivated Light Smoking class, there was a lower likelihood of respondents reporting daily smoking, high dependence, and heavy smoking as compared to the prior two classes. Similar to UHS, these patients reported lower likelihoods of past year quit attempts, endorsing quitting as high in importance, and reporting high confidence in

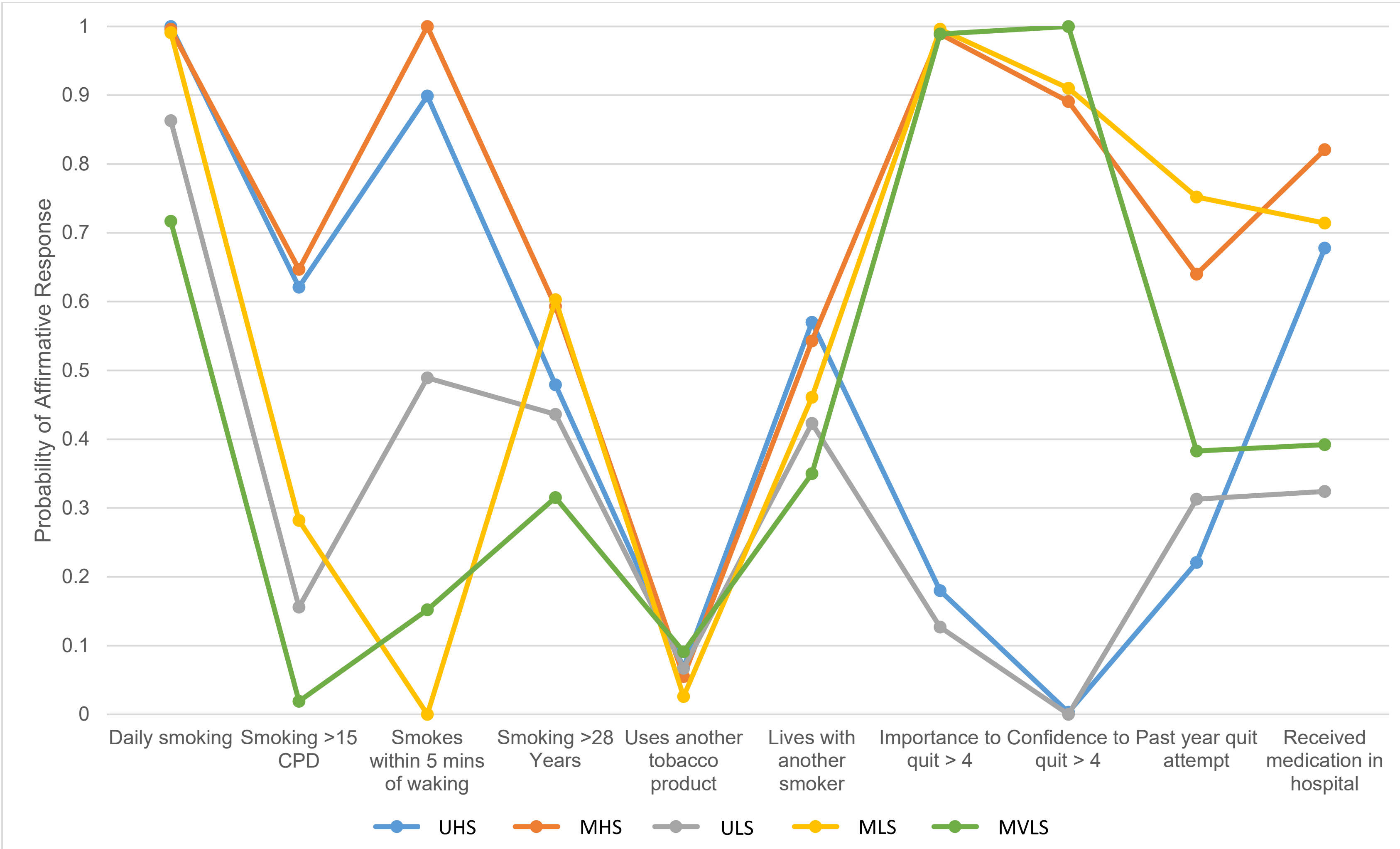

Figure 1. Probabilities of responding affirmatively to dichotomized variables in the LCA. *Note.* UHS = Unmotivated Heavy Smoking; MHS = Motivated Heavy Smoking; ULS = Unmotivated Light Smoking; MLS = Motivated Light Smoking; MVLS = Motivated Very Light Smoking. CPD = cigarettes per day.

Supplemental Table 1. *Model Fit Statistics*

2 class	3 class	4 class	**5 class**	6 class
AIC: 48307.899 BIC: 48444.137 SSA-BIC: 48377.407 Entropy: 0.890	AIC: 47709.651 BIC: 47917.253 SSA-BIC: 47815.568 Entropy: 0.756	AIC: 47517.389 BIC: 47796.354 SSA-BIC: 47659.716 Entropy: 0.687	AIC: 47451.463 BIC: 47801.791 SSA-BIC: 47630.198 Entropy: 0.701	AIC: 47408.786 BIC: 47830.477 SSA-BIC: 47623.930 Entropy: 0.698
	BLRT 3- vs 2-class: $p < .00001$	BLRT 4- vs 3-class: $p < .00001$	BLRT 5- vs 4-class: $p < .0001$	BLRT 6- vs 5-class: $p < .0197$

Note. AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion; SSA-BIC = Sample-size Adjusted BIC; BLRT = Bootstrapped likelihood ratio tests.

quitting. However, this class had lower probabilities than the first two of receiving medications while hospitalized.

Motivated Light Smoking (MLS); n = 895, 18.4%

The fourth identified class were nearly all smoking daily, although none reported high dependence. This group had a low probability of reporting heavy smoking, but high probabilities of receiving a medication while hospitalized, reporting a past year quit attempt, high importance of quitting, and high confidence in quitting.

Motivated Very Light Smoking (MVLS); n = 494, 10.2%

The final class identified had the lowest probability of daily smoking relative to the other classes. This class also had relatively low probabilities of reporting high dependence, high cigarette smoking, or receiving a medication while admitted. Despite this, probabilities of endorsing high importance of quitting and high confidence in quitting were high.

Predictors of Class Membership

Based on the distribution of racial identity within our patient sample, we collapsed race into three categories to use as predictors of class membership: white, black/African American, and other. Table 2 shows numeric counts of each characteristic per class and Table 3 presents unadjusted odds ratios (ORs) with 95% confidence intervals (CIs) for each class comparison.

Overall, black/African American patients were more likely to fall into ULS (OR = 1.88 [1.55 -2.29]), MLS (OR = 1.65 [1.37 - 1.97]), and MVLS (OR = 1.92 [1.54 - 2.38) compared to UHS. These patients were also less likely to fall into MHS compared to ULS (OR = 0.49 [0.40 - 0.60]), MLS (OR = 0.56 [0.47 - 0.68]), and MVLS (OR = 0.48 [0.39 0.60]). White patients were more likely to fall into MHS compared to ULS (OR = 1.83 [1.52 -2.21]), MLS (OR = 1.62 [1.37 - 1.92]) and MVLS (OR = 1.76 [1.43 - 2.17]). Additionally, white patients were less likely to be in ULS (OR = 0.62 [0.51 - 0.74], MLS (OR = 0.70 [0.59 - 0.82]), and MVLS (OR = 0.64 [0.52 - 0.79]), relative to UHS. Sex only had an effect on MHS relative to MVLS, such that males were less likely to fall into MHS (OR = 0.80 [0.65 - 0.98]).

Individuals who fell into MLS were more likely to have hypertension (OR = 1.32 [1.10 - 1.59]), diabetes (OR = 1.50 [1.18 - 1.91]), and congestive heart failure (OR = 1.66 [1.21 - 2.27]), but less likely to have cancer (OR = 0.71 [0.52 - 0.97]), compared to UHS. Those who had congestive heart failure were more likely to fall into MHS (OR = 1.46 [1.00 - 2.14]) compared to ULS, but less likely to fall into ULS (OR = 0.55 [0.37 - 0.81]) compared to MLS. Those who had a stroke were more likely to fall into ULS (OR = 1.97 [1.07 - 3.61]) and MLS (OR = 2.01 [1.12 - 3.60]), compared to MVLS. Finally, those who had diabetes were less likely to fall into MHS (OR = 0.62 [0.48 - 0.79]) compared to MLS, and those who had hypertension were more likely to fall into MLS (OR = 1.34 [1.05 - 1.71]) compared to MVLS.

Discussion

Inpatient TTPs have the ability to reach a broad range of patients to promote tobacco cessation. To examine these extensive, generalized programs, analytic strategies that account for multiple variables and identify natural patterns are required. The present analysis sought to characterize a large group of patients treated by the MUSC TTP based on responses during the bedside interview. Using LCA, 5 unique classes of patients emerged. In general, classes were differentiated based on smoking frequency and motivation to stop smoking, and were named as follows: Motivated Heavy

Table 2. *Patient Characteristics Within Class*

Full Sample *N* = 4854	UHS Unmotivated Heavy Smoking	MHS Motivated Heavy Smoking	ULS Unmotivated Light Smoking	MLS Motivated Light Smoking	MVLS Motivated Very Light Smoking
Characteristic (n, %)	***n* = 1396**	***n* = 1381**	***n* = 688**	***n* = 895**	***n* = 494**
Male (n = 2206)	640 (45.85%)	600 (43.45%)	310 (45.06%)	414 (46.31%)	242 (48.99%)
Black Race (n = 1480)	356 (25.50%)	335 (24.26%)	270 (39.24%)	323 (36.09%)	196 (39.68%)
White Race (n = 2628)	805 (57.66%)	840 (60.83%)	315 (45.78%)	437 (48.83%)	231 (46.76%)
Other Race (n = 746)	235 (16.83%)	206 (14.92%)	103 (14.97%)	135 (15.08%)	67 (13.56%)
Hypertension (n = 1353)	360 (25.79%)	383 (27.73%)	202 (29.36%)	282 (31.51%)	126 (25.51%)
COPD (n = 272)	93 (6.66%)	76 (5.50%)	37 (5.38%)	49 (5.47%)	17 (3.44%)
Diabetes (n = 616)	160 (11.46%)	150 (10.86%)	90 (13.08%)	146 (16.31%)	70 (14.17%)
Congestive Heart Failure (n = 355)	84 (6.02%)	109 (7.89%)	38 (5.52%)	86 (9.61%)	38 (7.69%)
Stroke (n = 243)	66 (4.73%)	69 (5.00%)	40 (5.81%)	53 (5.92%)	15 (3.04%)
Cancer (n = 418)	132 (9.46%)	127 (9.20%)	58 (8.43%)	62 (6.93%)	39 (7.89%)

Note. Percentages represent within class counts; counts for predictor variables are included for reference.

Table 3. *Patient Characteristics as Independent Predictors of Class Membership*

	Class Comparison *OR (95% CI)*									
Characteristic	**MHS vs UHS**	**ULS vs UHS**	**MLS vs UHS**	**MVLS vs UHS**	**MHS vs ULS**	**MHS vs MLS**	**MHS vs MVLS**	**ULS vs MLS**	**ULS vs MVLS**	**MLS vs MVLS**
Male	0.90 (0.78 - 1.05)	0.96 (0.80 - 1.16)	1.01 (0.86 - 1.20)	1.13 (0.92 - 1.39)	0.93 (0.77 - 1.12)	0.89 (0.75 - 1.05)	**0.80 (0.65 - 0.98)**	0.95 (0.77 - 1.16)	0.85 (0.67 - 1.07)	0.89 (0.72 - 1.11)
Black Race	0.93 (0.78 - 1.11)	**1.88 (1.55 -2.29)**	**1.65 (1.37 - 1.97)**	**1.92 (1.54 - 2.38)**	**0.49 (0.40 - 0.60)**	**0.56 (0.47 - 0.68)**	**0.48 (0.39 0.60)**	1.14 (0.93 - 1.40)	0.98 (0.77 - 1.24)	0.85 (0.68 - 1.07)
White Race	1.14 (0.98 - 1.32)	**0.62 (0.51 - 0.74)**	**0.70 (0.59 - 0.82)**	**0.64 (0.52 - 0.79)**	**1.83 (1.52 -2.21)**	**1.62 (1.37 - 1.92)**	**1.76 (1.43 - 2.17)**	0.88 (0.72 - 1.08)	0.96 (0.76 - 1.21)	1.08 (0.87 - 1.35)
Other Race	0.86 (0.70 - 1.06)	0.87 (0.67 - 1.11)	0.87 (0.69 - 1.10)	0.77 (0.57 - 1.03)	0.99 (0.77 -1.28)	0.98 (0.78 - 1.24)	1.11 (0.83 - 1.50)	0.99 (0.75 - 1.30)	1.12 (0.80 - 1.56)	1.13 (0.82 - 1.55)
Hypertension	1.10 (0.93 - 1.30)	1.19 (0.97 - 1.46)	**1.32 (1.10 - 1.59)**	0.98 (0.77 - 1.24)	0.92 (0.75 - 1.13)	0.83 (0.69 - 1.00)	1.12 (0.88 - 1.41)	0.90 (0.72 - 1.12)	1.21 (0.93 - 1.57)	**1.34 (1.05 - 1.71)**
COPD	0.81 (0.59 - 1.11)	0.79 (0.53 - 1.17)	0.81 (0.56 - 1.15)	**0.49 (0.29 - 0.84)**	1.02 (0.68 - 1.53)	1.00 (0.69 - 1.45)	1.63 (0.95 - 2.79)	0.98 (0.63 - 1.52)	1.59 (0.88 - 2.86)	1.62 (0.92 - 2.85)
Diabetes	0.94 (0.74 - 1.19)	1.16 (0.88 - 1.53)	**1.50 (1.18 - 1.91)**	1.27 (0.94 - 1.72)	0.81 (0.61 - 1.07)	**0.62 (0.48 - 0.79)**	0.73 (0.54 - 1.00)	0.77 (0.58 - 1.02)	0.91 (0.65 - 1.27)	1.18 (0.86 - 1.60)
Congestive Heart Failure	1.33 (0.99 - 1.79)	0.91 (0.61 - 1.35)	**1.66 (1.21 - 2.27)**	1.30 (0.87 - 1.93)	**1.46 (1.01 - 2.14)**	0.80 (0.60 - 1.08)	1.02 (0.70 - 1.51)	**0.55 (0.37 - 0.81)**	0.70 (0.44 - 1.11)	1.27 (0.85 - 1.90)
Stroke	1.06 (0.75 - 1.49)	1.24 (0.83 - 1.86)	1.26 (0.87 - 1.83)	0.63 (0.35 - 1.11)	0.85 (0.57 - 1.27)	0.83 (0.57 - 1.20)	1.67 (0.95 - 2.96)	0.98 (0.64 - 1.49)	**1.97 (1.07 - 3.61)**	**2.01 (1.12 - 3.60)**
Cancer	0.97 (0.75 - 1.25)	0.88 (0.63 - 1.21)	**0.71 (0.52 - 0.97)**	0.82 (0.56 - 1.19)	1.10 (0.79 - 1.52)	1.36 (0.99 - 1.86)	1.18 (0.81 - 1.71)	1.23 (0.85 - 1.79)	1.07 (0.70 - 1.64)	0.86 (0.57 - 1.31)

Note. Unadjusted models. OR = odds ratio; CI = Confidence interval. Bolded results indicate $p < .001$.

Smoking, Unmotivated Heavy Smoking, Motivated Light Smoking, Unmotivated Light Smoking, Motivated Very Light Smoking.

Of note, patients in all classes reported low rates of alternative tobacco use, which likely contributed to some overlap within the classes. This is evidenced by the entropy of .07, which is slightly lower than ideal. Had this variable been removed from the present model and the LCA re-run, it is likely that more distinct classes would have emerged. Future iterations of LCA within patient samples from this hospital system may improve in model fit with this adjustment; however, because of the evolving availability and popularity of alternative tobacco products, such as e-cigarettes (Rigotti et al., 2015; Zhu et al., 2017), polytobacco use among hospital patients should continue to be monitored and included in evaluations of patient characteristics. Indeed, prior LCA studies have demonstrated heterogeneity of tobacco product use and the association with dependence (Kypriotakis et al., 2018).

Demographic variables (gender and race) were tested as predictors of class membership. Consistent with population surveys, our sample of hospitalized smokers found that white patients were more likely to be classified in the heavy smoking subgroups groups, while black/African American patients were more likely to be classified in the lighter smoking groups (Trinidad et al., 2011). Despite lower average reported smoking frequencies, the black/African American patients in our sample had a higher prevalence of smoking-related illnesses, which is consistent with population studies (Park et al., 2011). Marginalized populations, such as black/African Americans, tend to have more barriers for accessing and receiving treatment resources for health conditions as well as smoking cessation. Additionally, a growing body of literature supports the notion that tobacco companies aggressively targeted these communities with menthol cigarettes (Alexander et al., 2016), leading to the tobacco-related health disparities present in population surveys and the current study.

In the present study, patients were more likely to be classified as Motivated Light Smoking (MLS) than Unmotivated Heavy Smoking (UHS) if they had hypertension, diabetes, and congestive heart failure indicated in the “problem list” on their medical chart. The lower frequency of smoking found among patients who reported a history of chronic illnesses is opposite to what might be expected given the well-established dose-dependent association between smoking and disease. However, there are several possible explanations that can explain this finding. First, the demographic makeup of these classes differ in ways that are consistent with both smoking frequency and chronic disease prevalence. Indeed, black/African Americans have higher rates of hypertension, diabetes, and congestive heart failure overall, and among those who smoke report smoking at lower rates compared to their white counterparts (Ho & Elo, 2013).

Another explanation might be that patients with a known history of chronic illnesses who are hospitalized will report smoking less, because they are more motivated to stop smoking, perhaps in response to a diagnosis of a smoking-related disease. This finding is partially supported by the observation that those with congestive heart failure were more likely to be classified into classes with higher levels of motivation to quit (MHS, MLS) than those with lower evidence of motivation (UHS, ULS). In addition, those with COPD, stroke, and diabetes were less likely to be categorized as Motivated Very Light Smoking (MVLS) compared to some other classes.

In general, our findings show that hospitalized patients who smoke and receive tobacco treatment are heterogeneous in terms of their smoking histories and motivation to quit. Understanding latent categories of patients provides insight for tailoring interventions and potentially improving tobacco treatment outcomes, consistent with suggestions from previously published LCAs on tobacco use that demonstrated significant heterogeneity of characteristics between classes of individuals who smoke (e.g., Sutfin et al, 2009). For instance, treatments may be tailored for the stage of change the hospitalized patients are in, or the degree of salience the teachable moment has on thoughts of changing smoking behavior. Differences in tobacco dependence characteristics within classes is consistent with previous research (Kypriotakis et al., 2018) and supports the use of personalized pharmacotherapy recommendations during admission and upon discharge. Our findings suggest subgroups based on smoking frequency and motivation to quit are moderated by race and history of smoking related diseases. Understanding these characteristics may inform recommendations to best mitigate withdrawal symptoms while remining mindful of other health symptomology that may be occurring. Our results also support maintaining inpatient treatment programs at hospitals, as they are able to have a broad impact on diverse patient populations. Program elements need not be specific or overly intensive, but rather can provide general support for patients, which allows for an increased number of patients who can receive treatment (Palmer et al., 2021). Programs should continue to conduct descriptive and quality improvement research to maintain funding resources and improve clinical services.

Limitations

There are several limitations of the present analysis that should be considered within the context of the results. First, the data are cross-sectional and therefore longitudinal transitions in smoking patterns, motivation, and the diagnosis of health conditions are unable to be determined. Second, there was no non-smoking control group (i.e., either never smoker or former smoker) used for reference, which limits interpretations of health risk to relative comparisons between those who currently smoke. However, the present study provides a foundation for which future research could develop longitudinal studies to assess smoking, chronic health conditions, and the role of interventions embedded within medical settings. Third, there are limitations associated with the use of LCA as used in this study. Dichotomizing continuous variables based on median split can result in a loss of information. Future research might consider latent profile analyses or latent transition analyses to assess more complex trends in patient data. An additional consideration is the lack of validation of the final model generated in the present study. That is, the classes that emerged from the LCA were not statistically confirmed on an additional sample, which reduces the generalizability of our findings. Future research can confirm these classes within the hospital system used in the present study as well as with samples from other hospitals. Missing data from the patient assessment interviews also introduce bias into the analyses. Finally, the influence of patient class on downstream measures of smoking cessation could not be assessed due to low response to our post-discharge IVR follow-up to assess smoking status.

Implications for Health Behavior Theory

Advanced, person-centered methodological approaches can be used to accurately an efficiently characterize and evaluate large samples. This study illustrates the application of such approaches to inform program evaluation. LCA was used to differentiate categories of patients receiving tobacco treatment from an inpatient hospital service. Among patients receiving a brief, inpatient tobacco treatment bedside consult, LCA identified 5 classes differing in smoking frequency and motivation to quit. Consistent with established estimates of tobacco-related health disparities, race/ethnicity and history of smoking-related health conditions were predictive of class membership in the present study. The varying compositions of patient classes suggest that multiple influences may be contributing to the tobacco use patterns in each class in addition to the associated health and sociodemographic conditions. With a better understanding of these associations, tobacco treatment interventions can become tailored to address specific needs.

At an individual level, there is evidence that brief, nonspecific tobacco treatment interventions embedded in an inpatient hospital admission are effective at initiating quit attempts and promoting abstinence, although there remains substantial room for improvement. Using a person-centered analytical approach to categorize patients allows for a more accurate assessment of patient characteristics and groupings. Future research can evaluate the efficacy of tobacco treatment interventions between these groups, and assess specific barriers to quitting. This knowledge will allow clinicians to tailor treatments to each groups' specific needs, thus improving outcomes. Broad interventions, such as the program described, may also help to address racial health disparities by providing access to treatment and specific resources to individuals who may otherwise have not had assistance with quitting tobacco. At the hospital or organizational level, LCA on large patient samples undergoing tobacco treatment can be used to obtain additional resources from administration and other key stakeholders. That is, LCA can be used to describe the general characteristics of patients engaging with the program at the hospital, and any differences in treatment delivery and outcomes that might exist between certain groups. Interventions may then be tailored for stage of change, most effective pharmacotherapy, and post-discharge resources to ensure patents receive comprehensive services that meet their specific needs. A strong program analysis may justify allocating funds, training, staff, grants, and other resources to improving the tobacco treatment program as a whole and for special populations (Palmer et al., 2021). Importantly, evaluating cost-savings as a result of changes in health outcomes following treatment is critical for retaining funding for tobacco treatment programs. Finally, findings from LCAs of hospital patients can be extended into the community, in that the patient sample represents the individuals in the surrounding area. Hospital systems and community organizations may collaborate to provide tailored smoking cessation services to the public to encourage post-discharge maintenance of tobacco abstinence, as well as develop smoking prevention programs for those who are risk of starting.

Discussion Questions

1. Findings indicate that patients receiving inpatient tobacco treatment can be grouped into distinct classes based on level of smoking and motivation to quit. Moreover, these classes vary in sociodemographic makeup and health conditions present. How might inpatient tobacco treatment interventions be tailored to address the specific characteristics of the patient classes found in the present study?
2. In the present study, different sociodemographic characteristics and health conditions were related to class membership. What should future researchers do to further evaluate the relationships between classes of patients

who smoke, sociodemographics, and tobacco-related health conditions?

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