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Patient Characteristics Predictive of Cardiac Rehabilitation Adherence

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Abstract

Purpose—Cardiac rehabilitation (CR) is a program of structured exercise and interventions for coronary risk factor reduction that reduces morbidity and mortality following a major cardiac event. Although a dose response relationship between number of CR sessions completed and health outcomes has been demonstrated, adherence with CR is not high. In this study we examined associations between number ofsessions completed within CR and patient demographics, clinical characteristics, smoking status, and socioeconomic status (SES).

Methods—Multiple LogisticRegression and Classification and Regression Tree (CART) modeling were used to examine associations between participant characteristics measured at CR intake and number of sessions completed in a prospectively collected CR clinical database (N=1658).

Results—Current smoking, lower-SES, non-surgical diagnosis, exercise-limiting comorbidities, and lower age independently predicted fewer sessions completed. The CART analysis illustrates how combinations of these characteristics (i.e., risk profiles) predict number of sessions completed. Those with the highest-risk profile for non-adherence (less than 65 years old, current smoker, lower-SES) completed on average 9 sessions while those with the lowest-risk profile (greater than 72 years old, not current smoker, higher-SES, surgical diagnosis) completed on average 27 sessions.

Conclusions—Younger individuals, as well as those who report smoking, economic challenges, or have a non-surgical diagnosis, may require additional support to maintain CR session attendance.

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Introduction

Cardiac rehabilitation (CR) is a program consisting of individualized, structured, progressive exercise sessions and behavioral and pharmacological interventions for coronary risk factor reduction that is highly effective at reducing morbidity and mortality rates following a myocardial infarction (MI) or coronary revascularization.[1-5] Cardiac rehabilitation participation is associated with a 20-30% reduction in cardiac re-hospitalizations and 26% decrease in cardiac mortality.[6]

Considering that CR is a highly effective treatment for reducing recurrent cardiac events, it is important to examine if patients are benefiting as much as possible from this effective service. Most insurance covers up to 36 sessions and the benefits of CR have been demonstrated to increase with the number of sessions attended, with each additional 6 cardiac rehabilitation sessions attended reducing risk of subsequent MI by 5-11%.[7, 8] Given the increasing health benefits of attending additional sessions it is imperative to determine which patients are at risk of being less adherent by completing fewer sessions.

Several patient characteristics have been associated with early drop out of CR. Those who did not have a surgical diagnosis complete fewer sessions[7-9] as do those with depressive symptoms.[10-12] Comorbidities, such as diabetes, peripheral vascular disease, obesity, and chronic obstructive pulmonary disease, appear to also predict fewer sessions completed.[13-16,8] Effects of smoking have been reviewed, with current smoking being a powerful predictor of fewer sessions completed.[17] Lower-socioecomonic status (SES), measured by income, education, or having subsidized insurance (e.g. Medicaid), may also predict fewer sessions completed.[8,10,16] However, data on effects on SES has largely been restricted to patients who are 65 or older (enrolled in Medicare). Evidence on effect of sex differences is mixed, with reviews of studies being unable to demonstrate a consistent direction of effect.[9,10] Age appears to have a modal relationship with number of sessions attended, with the very young and the very old being at risk to complete fewer sessions.[8,10] As is detailed above, a number of variables predicting early CR termination have been identified, however, it remains unclear how these variables may interact or whether certain risk-factor combinations are particularly strong predictors of dropout.

This study seeks to expand on the existing literature on predictors of number of CR sessions completed by examining the relative strength of the contributions of various factors, clinical and demographic, within a large, prospectively collected, clinical database. This study includes many characteristics that have previously been shown to be predictive of number of sessions completed but also expands upon the existing literature by including a measure of aerobic fitness (Peak Metabolic Equivalents) as well as focusing on socioeconomic status (SES). Often strongly associated with health-related behaviors, information regarding SES is not commonly collected in CR programs. Additionally, to facilitate examination of risk-factor combinations, or risk profiles, in predicting number of sessions completed we conducted a Classification and Regression Tree (CART) analysis. CART is a nonparametric procedure for dividing a population of interest into mutually exclusive subgroups based on a dependent variable of interest while identifying independent variables with the most explanatory power in accounting for that dependent variable. To our knowledge, no one has applied CART analyses to the issue of cardiac rehabilitation attendance allowing for a unique opportunity to rank patient characteristics based on relative importance and examine cumulative effects of different characteristics on number of sessions attended.

Materials and Methods

Participants

Data were extracted from a prospectively collected clinical database. The cohort was 1658 patients who had at least an entry stress test at the CR program at the University of Vermont Medical Center on January 1, 2010or later and who completed or dropped out of the program by December 31, 2014.

The primary outcome of interest was number of sessions completed out of a possible 36. The following variables were included in the analyses: age, sex, CR qualifying diagnosis (surgical or non-surgical), self-reported smoking status (current smoker vs. non/former smoker), socioeconomic status (lower-SES vs. higher-SES as defined below), body mass index (BMI), depression score (Geriatric Depression Scale, 0-4 vs. 5+), aerobic fitness level at intake (Peak Metabolic Equivalents), and exercise–limiting comorbidities (none or minimal vs. moderate or severe).

Billing information extracted from electronic health records was used to determine SES status. Lower-SES was defined as having Medicaid insurance during CR participation. Current smoking was defined as reporting current smoking (within past 30 days) at intake to the CR program. Attendance data for former (≥100 cigarettes lifetime but not past 30 days) and never smokers (< 100 cigarettes lifetime) were not significantly different (data not shown) and were thus combined into one group (former/never smokers). To assess aerobic fitness, a symptom-limited exercise tolerance test was performed to determine peak metabolic equivalents ($METs_{peak}$). $METs_{peak}$ were estimated based on the highest speed and grades achieved during the exercise test[18] and were available for 1459 patients (88%). The exercise- limiting comorbidities score was calculated as a combination of the presence and severity of conditions that could limit activities within the CR program and consisted of COPD, PVD, orthopedic problems, and CVA/stroke. Patients were grouped as having either no comorbidities or comorbidities that would minimally impact exercise capacity versus patients who had a comorbidity or a combination of comorbidities that moderately or severely interfered with CR physical activities. Depression status was determined based on scores from the Geriatric Depression Scale – short form (GDS).[19] A score of 0-4 is considered in the normal range while 5 or higher is suggestive of depression. Depression scores were available for 968 (58%) of the patients included in the database.

Statistical methodology

Frequencies and descriptive statistics were generated for independent variables with complete or relatively complete data: sex, age, BMI, diagnosis, smoking status, SES, number of comorbidities, and $METs_{peak}$. Univariate tests of association with the primary dependent variable (number of sessions completed) were conducted and variables significantly related to the outcome were then used in multiple regression analysis. An initial model predicting number of sessions was fit using independent variables univariately associated with the outcome. Any variable that did not contribute significantly to predicting the outcome was deleted from the model. Once a tentative final model was determined, variables that had been eliminated earlier in the process were reintroduced, one at a time, and retained only if they contributed to the model in the presence of the previously significant predictors. Once the next iteration of a final model was determined, all possible interactions were tested, one at a time. Since no interaction contributed to the model, the final model consisted entirely of main effects. Final beta estimates and 95% confidence intervals were generated. A normal probability plot of jackknife residuals, a plot of jackknife residuals versus predicted values of number of sessions, plots of jackknife residuals versus each predictor, plots of leverage and Cook's *D*, and correlation matrices between the independent variables and the dependent variable, as well as across independent variables, were generated to examine outliers, homogeneity of variance across the outcome variable, normality, linearity, and collinearity. All analyses were conducted using SAS 9.4 (SAS Institute, Cary, NC). All tests used a 5% Type I error level.

A Classification and Regression Tree (CART) analysis[20] was used to quantify which of the variables identified in logistic regression analyses were most important in predicting number of sessions completed and how combinations of those variables (risk profiles) affected number of sessions completed. CART is a nonparametric procedure for dividing a population of interest into mutually exclusive subgroups based on a dependent variable of interest, such as number of sessions in the current study[21] and, in the process, identifying independent variables with the most explanatory power in accounting for that dependent variable. The process begins by identifying the single most important independent variable for dividing the total sample (parent node) into two groups (child nodes), using a predetermined branching criterion. Nodes are split based on their purity using the Gini impurityfunction.[20] A "pure" node has no variability in the dependent variable. A completely "impure" node has a conditional probability of $p(k|t) = 0.5$, where k refers to the dependent variable and t refers to the node.[22] A splitting or branching criterion "selects the split that has the largest difference between the impurity of the parent node and a weighted average of the impurity of the two child nodes."[21] We used the Gini impurity function to split nodes, repeating the process recursively with every subsample, until the subsample reached a minimum size or no further splits could be made. The tree was built using R's rpart package.[23,24] A fully saturated tree was produced initially, and then pruned by selecting the complexity parameter that minimized cross-validation error and setting a minimum sample size in terminal nodes (leaves) of n = 33. A hierarchy of variable importance was also generated.

Results

Univariate analyses

Patient characteristics can be seen in Table 1. Number of sessions completed differed significantly by all of the measured characteristics except sex and depression score. Younger age, lower- SES, having a non-surgical diagnosis, $METs_{peak}$, having exercise-limiting comorbidities, BMI, and being a current smoker were significantly associated with completing fewer sessions and were included in the subsequent multivariate model.

Multivariatelogistic regression analyses

Smoking status, SES, age, severity of comorbidities, and qualifying diagnosis contributed independently to predicting number of sessions completed in multivariate modeling (Table 2). $METs_{peak}$ and BMI were not significant independent predictors. Age and higher number of comorbidities were associated positively with number of sessions, while a non-surgical diagnosis, being a smoker, and lower SES were negatively associated with number of sessions.

Classification and regression tree (CART) analysis

The CART analysis created a hierarchy of the patient characteristic variables based on their level of importance in predicting number of sessions completed. Age was identified as the strongest predictor, followed by smoking status, SES, and then diagnosis (surgical or non-surgical). Figure 1 shows how combinations of different patient characteristics predict number of sessions attended. The node at the top of the figure represents the entire sample (n = 1,658) and the overall average number of sessions completed (20). The first branching of the sample was based on age, the strongest predictor. This split the sample into those less than 65 (52% of the sample and an average of 17 sessions completed) and those 65 or older (48% of the sample and an average of 24 sessions completed). The next most important characteristic for both the younger and older groups is being a current smoker, which predicts an average of eight fewer sessions completed than in former/never-smokers. This branching continues until further splitting of the sample would not result in significant improvement in the model. Nodes where further iterations are not informative are labeled terminal nodes and are located in the bottom two rows of Figure 1. These terminal nodes can be thought of as risk profiles that represent how many sessions a patient with that particular set of characteristics completed. Overall, the model identified 12 terminal nodes or risk profiles. The number of sessions completed within these different nodes ranged from a low of 9 for patients below 65 years of age who were current smokers and lower-SES to a high of 27 sessions completed for patients above the age of 72 who were nonsmokers, higher-SES, and had a surgical diagnosis.

Discussion

The results of our analyses demonstrate that current smoking, lower-SES, younger age, and a non-surgical qualifying diagnosisare independent, robust predictors of completing fewer sessions of CR. The most powerful predictor of number of sessions completed was whether a patient was 65 or older. Smoking status and SES were also strong independent predictors of number of sessions completed. Number of sessions completed ranged from a low of only 9 to a high of 27 sessions depending on the combination of patient characteristics. Some additional interesting patterns are discernible from CART analyses. For example, being a current smoker highly restricts the number of sessions completed. Any variable combination that includes current smoking predicts no more than 16 sessions completed. Alternatively, being in the younger (<65 years) group allows for the greatest effect of other variables.

Within the younger group, number of predicted sessions completed varies from 9 to 22 based on which other variables are present. Being in the older group (65+) seems the most protective, with all combinations within that first division predicted to complete at least 16 sessions. Current smoking and lower-SES are also less predictive in the older populations, likely due to the reduced number of smokers and lower-SES patients in the older age bracket. Not surprising, as smoking and lower SES are associated with reduced longevity.

Two of the strongest predictors of completing fewer sessions were being a current smoker and having lower-SES. This is unfortunate as these are also two populations that are at relatively increased medical risk following a cardiac event and would likely benefit most from additional sessions. Smokers, for example, are at especially high risk for subsequent morbidity and mortality following acute coronary events.[25] Lower-socioeconomic (SES) populations are also generally higher risk patients having greater rates of smoking, higher fat diets, lower levels of fitness, more hypertension, higher prevalence of type 2 diabetes mellitus, and are more likely to be obese than more affluent populations.[26-30] As would be expected, given high risk profiles, smokers and lower-SES patients are also more likely to be rehospitalized and have higher rates of mortality following an MI than their non-smoking, more affluent counterparts.[25-27,31,32] Accordingly, these higher-risk subgroups should be specifically targeted and encouraged to not only enter CR but also complete the recommended duration in order to receive the greatest benefit possible.

Given the importance of smoking status and SES, with their clinical risk implications and their implications for number of CR sessions completed, they are both inadequately measured in many clinical settings. Despite being one of the strongest predictors of future cardiac events[33,34], smoking is almost never objectively measured in clinical settings, such as with breath carbon monoxide or urine cotinine, most clinicians rely on self-reported smoking behavior. SES is also rarely recorded clinically. Clinics may avoid recording SES due to concerns about patient privacy or due to it not being viewed as clinically significant, despite SES being a predictor of many health-related behaviors.[35-37]

As lower-SES is a predictor of many negative health behaviors, perhaps it is not surprising that it is also a predictor of completing fewer CR sessions. What might be unexpected is that both smoking status and SES independently predict number of sessions completed with current smoking being the stronger predictor of the two variables. On a theoretical level this appears reasonable as one might expect that the best predictor of a negative health behavior is participation in another negative health behavior. This does have support in the literature. For example, in studies of treatment for drug dependence patients who smoked were less stable than those who did not, with smoking being a strong predictor of drug use and treatment success.[38,39] Analyses of national survey data in Canada also support this idea, with the greatest correspondence between unhealthy behaviors being between smoking and physical inactivity and the second most common between smoking and drinking.[40] This pattern also bears out in the area of medication adherence, where current smoking is a strong predictor of statin non-adherence.[41] Similar effects can be seen in other studies of medication adherence in different populations.[42,43]

As research in predictors of CR attendance continues it is becoming increasingly clear which groups are at high risk for completing relatively few sessions. However, what needs further clarification is the cause of dropout. One common barrier for the younger patients and for working lower-income patients is the hardship of attending a program multiple times weekly, a program that is often open only during usual working hours. Many patients may work in a job that does not allow the flexibility to attend a program with limited hours. The barriers for attendance among those who smoke could be diverse. Those who smoke may believe that attending CR does not have enough benefit to be worth the effort, may have lower tolerance to exercise, may have other more pressing health concerns, or may not feel they are getting any benefit from attending CR.[44,45] If the appropriate barriers within these various groups are identified CR staff can determine what interventions may be most useful, whether it is more education for the patient on the benefits of CR, a more intensive smoking cessation program, being open outside of normal working hours one day a week, or offering incentives for program completion.[17,46] Smoking cessation interventions should be a particularly high priority given the strong associations between current smoking and both high morbidity and mortality combined with strong associations with poor CR attendance

This study does have some limitations that should be mentioned. Smoking status was based on self-report, which likely underestimates prevalence. Medical comorbidity scores were determined based on clinical definitions at intake, we were not able to determine whether comorbidities actually caused symptoms during exercise sessions. Additionally, depression scores were not available for a large portion of the population and the population was restricted to a single clinical site. Despite these limitations the findings of this study appear robust and could serve to inform clinicians and policy makers. Individuals who report smoking or financial challenges at CR intake, especially younger patients, will likely require additional support to complete the CR program. Patients in these higher-risk groups should be queried about potential barriers to participation and provided with information about all available forms of assistance. Additionally, as smoking is such a strong predictor of early drop out, increased support for cessation could potentially help maintain participation in CR. Given the high-risk profiles of both low-SES populations and those who smoke, intense interventions should be provided to help encourage these patients to enter and complete CR.

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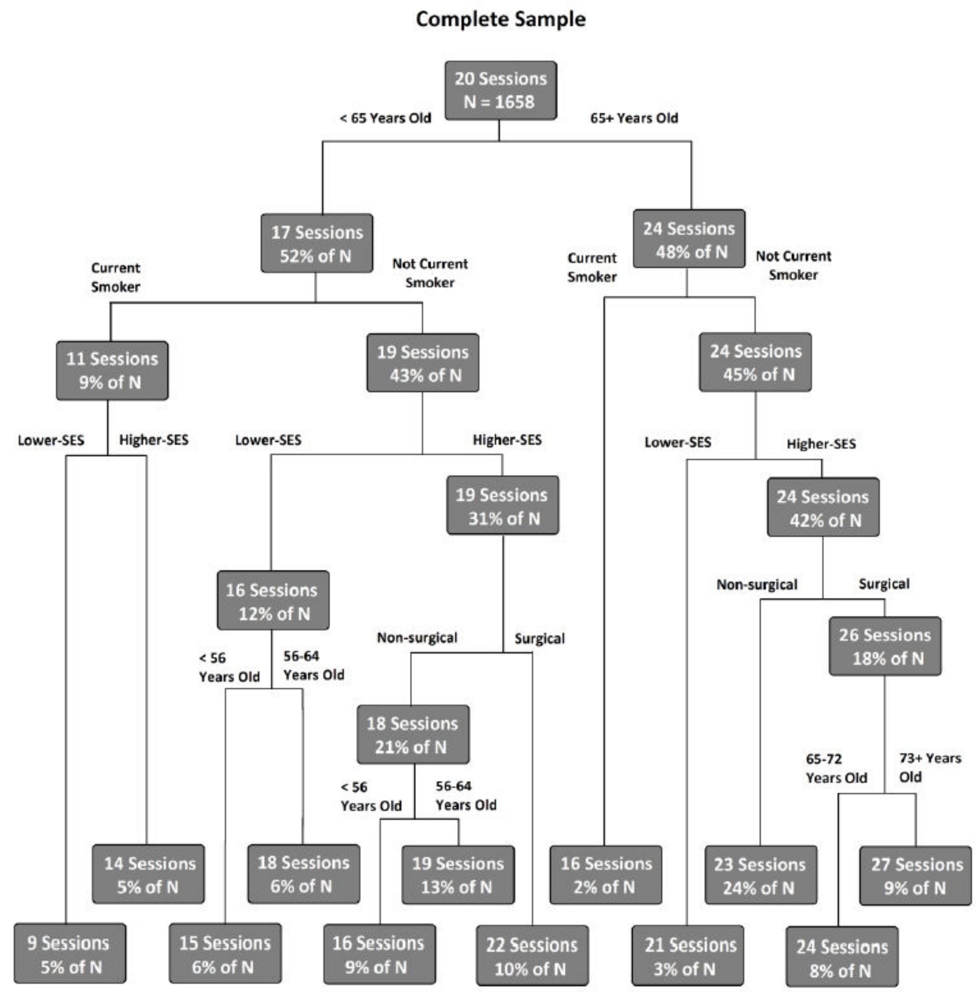

Figure 1.

Classification and regression tree (CART) analysis showing cumulative effects of patient characteristics on number of sessions attended.

Table 1

Baseline Characteristics and p-Values of Univariate Tests Predicting Number of Sessions

	All (*n* = 1,658)	***p***
Sex		
Female	451 (27.20%)	0.862
Male	1207 (72.80%)	
Age (years) (*M* ± *SD*)	63.86 ± 11.58	<0.001
BMI (*M* ± *SD*)	29.59 ± 5.94	<0.001
Diagnosis		
Nonsurgical	1041 (62.79%)	<0.001
Surgical	581 (35.04%)	
Smoking status		
Never or former	1459 (88.00%)	<0.001
Current	190 (11.46%)	
SES		
Higher	1302 (78.53%)	<0.001
Lower	356 (21.47%)	
No. comorbidities		
0-2	1389 (83.78%)	<0.001
3+	269 (16.22%)	
estMETs (*M* ± *SD*)	7.17 ± 2.93	<0.001
Depression (*M* ± *SD*)*	2.99 ± 2.86	0.156
No. sessions (*M* ± *SD*)	20.28 ± 13.65	

*Data were missing for 690 participants (42%).

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Table 2

Predictors of Number of Sessions

	Model 1	Model 2	
	ß	*ß*	95% CI
Intercept	18.88 ***	15.68 ***	[11.00, 20.36]
Age	0.16 ***	0.15 ***	[0.09, 0.21]
BMI	-0.07		
Diagnosis	-1.92 **	-2.25 ***	[-3.58, -0.93]
Smoker	-6.11 ***	-5.83 ***	[-7.92, -3.74]
SES	-3.50 **	-3.84 ***	[-5.47, -2.20]
Comorbidities	2.88 **	2.41 **	[0.68, 4.14]
estMETs	-0.23		
R^2	0.106	0.094	
F	24.36 ***	33.37 ***	

Note. CI = Confidence interval. Surgical is the reference for diagnosis. Never/Former smoker is the reference for smoker. Higher SES is the reference for SES. Low (0-2) is the reference for comorbidities.

* $p < .05$.

** $p < .01$.

*** $p < .001$.