Understanding Who Benefits at Each Step in an Internet-Based Diabetes Self-Management Program: Application of a Recursive Partitioning Approach

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Background**. Efforts to predict success in chronic disease management programs have been generally unsuccessful. **Objective**. To identify patient subgroups associated with success at each of 6 steps in a diabetes self-management (DSM) program. **Design**. Using data from a randomized trial, recursive partitioning with signal detection analysis was used to identify subgroups associated with 6 sequential steps of program success: agreement to participate, completion of baseline, initial website engagement, 4-month behavior change, later engagement, and longer-term maintenance. **Setting**. The study was conducted in 5 primary care clinics within Kaiser Permanente Colorado. **Patients**. Different numbers of patients participated in each step, including 2076, 544, 270, 219, 127, and 89. All measures available were used to address success at each step. **Intervention**. Participants were randomized to receive either enhanced usual care or 1 of 2 Internet-based DSM programs: 1) self-administered, computer-assisted self-management and 2) the self-administered program with the addition of enhanced social support. **Measurements**. Two sets of potential predictor variables and 6 dichotomous outcomes were created. **Results**. Signal detection analysis differentiated successful and unsuccessful subgroups at all but the final step. Different patient subgroups were associated with success at these different steps. Demographic factors (education, ethnicity, income) were associated with initial participation but not with later steps, and the converse was true of health behavior variables. **Limitations**. Analyses were limited to one setting, and the sample sizes for some of the steps were modest. **Conclusions**. Signal detection and recursive partitioning methods may be useful for identifying subgroups that are more or less successful at different steps of intervention and may aid in understanding variability in outcomes. **Key words:** diabetes self-management; interactive media; computer; prediction; health literacy; numeracy; Latino.* ***(Med Decis Making 2014;34:180–191)

The continued rise in the number of patients with type 2 diabetes is increasing the burden on health care systems in the United States and globally.[1,2] Diabetes self-management (DSM) programs have been found to be effective in helping individuals make the behavioral adjustments necessary to achieve and maintain optimal control of their hemoglobin A1c (HbA1c), blood pressure, and cholesterol levels,[3] but widespread adoption of these programs by primary care providers has not been achieved.[4,5] Provider reluctance to offer DSM programs as part of routine care has been attributed to lack of time, reimbursement, and resources[6]; however, qualitative research has shown that providers also have doubted the efficacy of such programs and lacked confidence in their own skills to provide the necessary self-management support.[7]

DSM interventions delivered via interactive media (IM), including Internet and telephone-based

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interventions, have potential to address some key patient and provider barriers by offering DSM education and behavioral support to patients outside of the clinic visit.[8] However, several studies have shown that the effectiveness of these IM-based programs may depend on contact and reinforcement from the health care team.[9,10] Provider beliefs about the efficacy (or lack of efficacy) of DSM programs, whether they are delivered in person or online, are not surprising, given the great variability in outcomes for patients participating in these programs, evaluations of which often report mixed results.[10,11] Patients' abilities to successfully make and maintain the many lifestyle changes necessary to manage diabetes have been shown to vary based on culture, language, health literacy, income, comorbidities, and social support.[12,13] Minority and low-income populations, who bear the highest burden of chronic illness in the United States, may benefit the least from ''evidence-based'' DSM programs.[2,14,15] Internet-based programs introduce another potential barrier, particularly for older and lower-income patients, but more recent reports on the ''digital divide'' and increased adoption of electronic medical records, mobile applications, and patient portals as a routine part of delivering primary care, as well as widespread adoption of Internet-enabled smartphones, are rapidly closing this gap.[14,16–18]

Improving understanding of patient characteristics associated with variations in patient participation, engagement, and outcomes in Internet-mediated DSM programs may help predict which patients will benefit from these programs and who may need different or additional forms of DSM support. Identification of who participates and benefits from Internet-based DSM programs could assist in focusing health care time and resources in a way that maximizes outcomes and reduces health disparities for individuals with diabetes. Another challenge in understanding patient characteristics associated with program participation is that often very little information is available on nonparticipants.

Analytic methods for identifying homogeneous subgroups of patients who will enroll in, engage with, and benefit from online DSM programs are not commonly used. Studies that use linear regression models, including our own attempts to understand who benefits the most from specific DSM programs,[19,20] have not been able to identify robust factors related to program success. One reason may be that DSM programs consist of multiple steps that together contribute to behavior change and future health outcomes. Individual variation in successful completion of each of these steps may be related to different patient characteristics. Linear regression modeling also may not be the optimal way to conceptualize the amount of independent variance accounted for in outcomes by multiple predictors. Kiernan and others[21] compared logistic regression with signal detection to understand whether patients could be classified into specific risk factor subgroups with similar outcomes. They found that only signal detection methodology (SDM), a recursive partitioning approach, was useful for identifying individuals who were homogeneous in both risk predictors and outcomes.

As a system of classification for predicting a dichotomous event,[22] signal detection principles have been applied to a variety of disciplines, including medicine,[23–25] epidemiology and public health,[26,27] and psychology.[28–30] The assumptions of signal detection theory can be evaluated statistically with a relative (or receiver) operating characteristic (ROC).[24,29] An ROC curve represents the relative proportion of times that an adverse outcome was correctly chosen by the diagnostic system (true positives, or ''hits'') to the proportion of times that an adverse outcome was incorrectly chosen (false positives, or ''misses'') for various cutoffs, thus facilitating consideration of the relative importance of false-positive v. false-negative identifications. By using an ROC curve, it is possible to determine optimal predictors, as well as their optimal cut points, for classifying subpopulations on the binary outcome. Signal detection methods can be incorporated within the broader class of analyses involving recursive partitioning. Repeated application of SDM-guided partitioning, to the subsets identified in the previous stage, results in a ''classification tree'' that identifies different subgroups that are homogeneous with respect to the classification features and that have widely varying outcome proportions.

The objectives of this study were both substantive and methodologic and included a) to use a signal detection recursive partitioning approach to understand the variation in patient outcomes in an evidence-based, online DSM program; b) to identify patient factors associated with homogeneous behavioral and health outcomes at different steps of participation, including enrolling in the online DSM program, completing baseline assessments, initial engagement with the Internet DSM program, initial behavior change, longer term engagement in the DSM program, and longer term behavior change-maintenance; and c) to discuss implications for research and practice.

Table 1 Characteristics of Study Participants (N = 462) Across Conditions.

Characteristic	Total	EUC (n = 132)	CASM (n = 168)	CASM+ (n = 162)	Significance[a]
Age, mean (SD), y	58.4 (9.2)	58.7 (9.1)	58.7 (9.3)	57.8 (9.3)	0.618
% Female sex	49.8	51.5	44.6	53.7	0.231
Race, %					0.525
American Indian/Alaska Native	6.7	11.1	4.9	4.8	
Asian	1.6	1.6	1.9	1.4	
Black or African American	15.4	12.7	14.8	18.4	
White	72.0	70.6	74.1	70.7	
Latino ethnicity	21.8	16.8	25.3	25.3	0.178
Income, %					0.241
Less than $49,999	47.3	50.4	45.7	46.0	
$50,000–$89,999	35.2	36.6	33.5	35.7	
$90,000 or more	17.5	13.0	20.6	18.2	
High school or less education, %	19.1	13.0	19.9	23.6	0.069
Low-moderate health literacy, %	5.9	7.6	6.0	4.3	0.495
Numeracy, mean (SD)	4.31 (1.0)	4.32 (0.8)	4.21 (1.1)	4.39 (1.0)	0.720
Computer use, h/wk, %					0.190
Never to 2½	16.3	15.1	16.6	16.6	
3–6½	17.7	21.2	20.2	12.4	
7–8½	6.1	4.5	5.4	8.0	
9+	60.0	59.1	57.7	63.0	
Smoke cigarettes, %	10.8	9.1	10.1	13.0	0.531

EUC, enhanced usual-care control condition; CASM/CASM+, computer-assisted self-management intervention.
[a]One-way analysis of variance or χ^2 test, as appropriate.

METHODS

Participants and Setting

The study was carried out in 5 primary care clinics within Kaiser Permanente Colorado (KPCO). Clinics were selected based on variability in size, location, and socioeconomic status of neighborhood and to maximize the percentage of Latino patients. Recruitment procedures and patient characteristics are described in detail in Glasgow and others.[31] All procedures were approved by the KPCO institutional review board. Data were collected between April 2008 and August 2012 and analyzed in 2012.

As shown in Table 1, 462 participants completed baseline and were randomized into 3 arms of the study. Participants had similar characteristics across conditions at baseline. Participants were overweight or obese (mean [standard deviation (SD)] body mass index [BMI] = 34.6 [6.6] kg/m^2), had other chronic conditions, and were moderately diverse on sociodemographic variables (e.g., 22% Latino, 15% African American, and 7% American Indian/Alaskan Native).

Intervention

A patient-randomized practical effectiveness trial[32] was conducted to evaluate 2 Internet-based DSM programs relative to enhanced usual care (EUC). The interventions were a) self-administered, computer-assisted self-management (CASM), based on social-ecological theory[33] and the ''5 As'' self-management model,[34] and b) the CASM program with the addition of enhanced social support (CASM+). The interventions, described in more detail in the study's main outcomes article,[20] included a graphic display of the patient's HbA1c, blood pressure, and cholesterol results; a moderated forum; and community resources for diabetes self-management and healthful lifestyles. Participants were asked to select initial, easily achievable goals to improve physical activity, eating patterns, and medication taking and to record their progress using the tracking section of the website. After 6 weeks, participants created personalized ''action plans'' for healthful eating, physical activity, and medication taking. CASM+ participants received all aspects of the CASM intervention with the addition of 2 follow-up calls from an interventionist and an invitation to attend 3 group visits with other participants in the same study condition. For the present analyses, CASM and CASM+ groups were combined, as there were no significant differences between conditions on behavioral, psychosocial, or biological outcomes.[20] EUC provided computer-based health risk

Table 2 Steps of the Diabetes Self-Management Program and Potential Predictors of Success

Steps of the Diabetes Self-Management Program	No	Yes
Step 1: Agree to participate (of those eligible)?	1532 (73.8)	544 (26.2)
Step 2: Complete baseline assessment?	82 (15.1)	462 (84.9)
Step 3: Engage in intervention website at least monthly from baseline to 4 months?	51 (18.9)	219 (81.1)
Step 4: Improve eating and/or exercise habits (≥50% of 1 SD) at 4 months?	92 (42.0)	127 (58.0)
Step 5: Engage in website at least bimonthly months 5–12?	38 (29.9)	89 (70.1)
Step 6: Maintain behavioral improvements at 12 months?	41 (46.1)	48 (53.9)

Values are presented as number (%). Set 1 (steps 1–2): age, sex, race, Latino ethnicity, income, education, cigarette smoking, systolic blood pressure, hemoglobin A1c, and body mass index. Set 2 (steps 3–6): age, sex, Latino ethnicity, income, education, cigarette smoking, systolic blood pressure, diastolic blood pressure, blood pressure mean arterial pressure, marital status, health literacy, number of comorbidities, computer experience, 10-year heart disease risk, Summary of Diabetes Self-Care Activities score, regimen distress, Patient Assessment of Care for Chronic Conditions score, Chronic Illness Resources Survey total score, caloric expenditure per week in physical activity from the CHAMPS instrument, percent energy from fat intake derived from the National Cancer Institute screener, eating habits score from the Starting The Conversation instrument, numeracy, number of primary care physician contacts during the study (also for steps 4–6: weekly v. nonweekly engagement in the intervention website from baseline to 4 months). SD, standard deviation.

appraisal feedback and recommended preventive care behaviors using the same contact schedule as the CASM conditions but did not include the key intervention procedures.

As detailed elsewhere, the combined Internet-based conditions improved health behaviors significantly v. usual care at 4 months[31] and 12 months[35] postbaseline, and all conditions improved moderately on biological and psychosocial outcomes.

Measures

For the present analyses, 6 dichotomous outcomes were created (Table 2), each using different numbers of patients (Figure 1) and different variable sets, as follows: 1) agreed v. declined to participate in the study (among those eligible), 2) completed v. did not complete baseline assessment, 3) visited the intervention website from baseline to 4 months at least monthly v. less than monthly (intervention participants only), 4) improved on 1 targeted DSM behavior (eating and/or exercise habits) by at least 50% of 1 SD v. did not improve at 4 months postbaseline (although medication taking was a third DSM behavior targeted in the study, it was not included in the present analyses because not all patients took medications) (intervention only), 5) visited the intervention website from 5 to 12 months at least bimonthly v. less than bimonthly (intervention only), and (6) maintained (by at least 50% of 1 SD) v. did not maintain behavioral improvement at 12 months postbaseline (intervention only). These cut points were set a priori or, when distributions prohibited use of a priori cut points, established based on resulting distributions in the outcome variable used for categorization prior to analyses. The second step—completed v. did not complete baseline assessments after initially agreeing to participate—may seem unusual and is typically not reported in Internet intervention or DSM studies, but it was important in this study, given that 15% of those initially agreeing did not complete baseline assessments despite repeated contacts. This ''no-show'' rate—or higher—has been reported in other recent Internet-based and in-person behavior-change programs.[36,37]

Two sets of variables were used as potential predictors of the 6 binary outcomes.

Potential predictors of participation and baseline assessment completion

A limited number of variables (set 1) derived from electronic patient medical records were used to predict study participation and baseline assessment completion. These variables were age, sex, race, Latino ethnicity, income, education, cigarette smoking, systolic blood pressure, hemoglobin A1c, and BMI.

Potential predictors of intervention success

A larger number of variables (set 2) were available to predict later steps among the 331 intervention participants. Derived from electronic medical records, internet DSM program usage statistics, and baseline participant surveys, these variables were age, sex, Latino ethnicity, income, education, cigarette smoking, systolic blood pressure, diastolic blood pressure, mean arterial pressure, marital status, health literacy,[38] numeracy,[39] number of comorbid conditions, usual level of weekly computer use, 10-year heart disease risk, Summary of Diabetes Self-Care Activities score,[40] regimen distress,[41] Patient Assessment of Care for Chronic Conditions score,[42] Chronic Illness Resources Survey total score,[43] baseline caloric

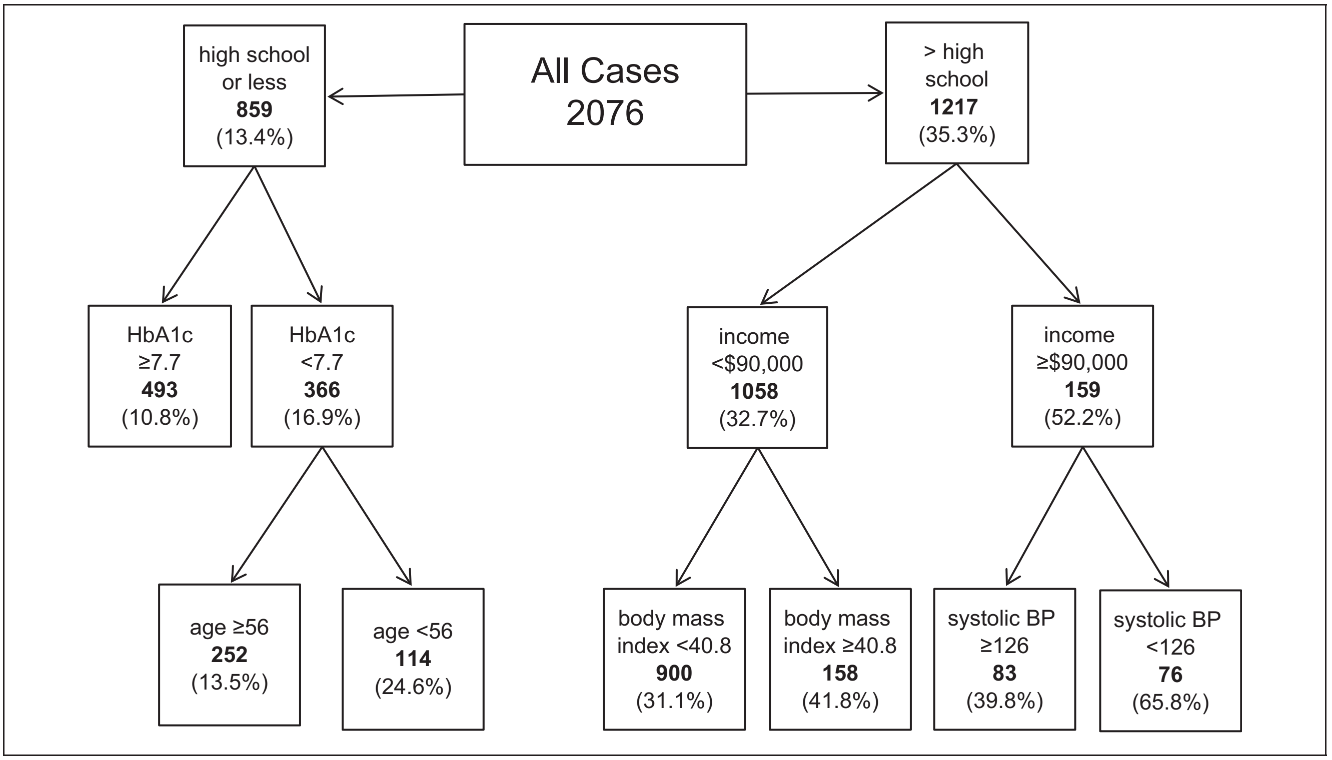

Figure 1 *Education, hemoglobin A1c (HbA1c), income, body mass index, and systolic blood pressure (BP) were significant predictors of participation.*

expenditure per week in physical activity from the CHAMPS instrument,[44] baseline percent energy from fat intake from the National Cancer Institute screener,[45] baseline eating habits score from the Starting The Conversation instrument[46] with higher scores indicating more healthful eating habits, number of primary care physician contacts during the study, and level of engagement in the intervention website.

In each set of analyses, all available variables were included in the analyses.

Analyses

SDM[21,47] was employed with the use of ROC4 software (Mental Illness Research Education and Clinical Center, Stamford, CT; ROC4 is available for free download at http://www.stanford.edu/~yesavage/ROC.html; the theory behind the program, including formulas for the software calculations, was derived from Kraemer[23]) to identify groups of patients who benefited at 6 steps of the diabetes self-management program. SDM uses ROC curves, adapted from an engineering context for use in general biobehavioral contexts, and an iterative approach to identify nonoverlapping, homogeneous, and maximally differentiated groups on dichotomous outcomes. The program's algorithm is more concise than the algorithms in standard categorization tree programs in that it uses kappa (rather than, e.g., the odds ratio) to minimize false positives and false negatives, resulting in fewer superfluous "branches."[23,48] An empirical ROC curve is employed rather than a fitted curve to avoid potentially untrue distribution assumptions. In the present analyses, sensitivity and specificity were weighed equally; that is, false positives and false negatives were weighted the same, and neither was emphasized. The significance threshold for predictor cut points was $P < 0.01$. Separate analyses were conducted for each of the 6 steps of the study, first with listwise data sets excluding cases with missing values and then with data sets in which missing values were imputed using NORM software multiple-imputation procedures.[49] As shown in Table 2, only those subjects who "succeeded" in the prior model were entered in subsequent models; thus, the number of subjects declined steadily across the steps. Results of the full (imputed) data set analyses are primarily presented here; listwise findings are noted where they differed from imputed results.

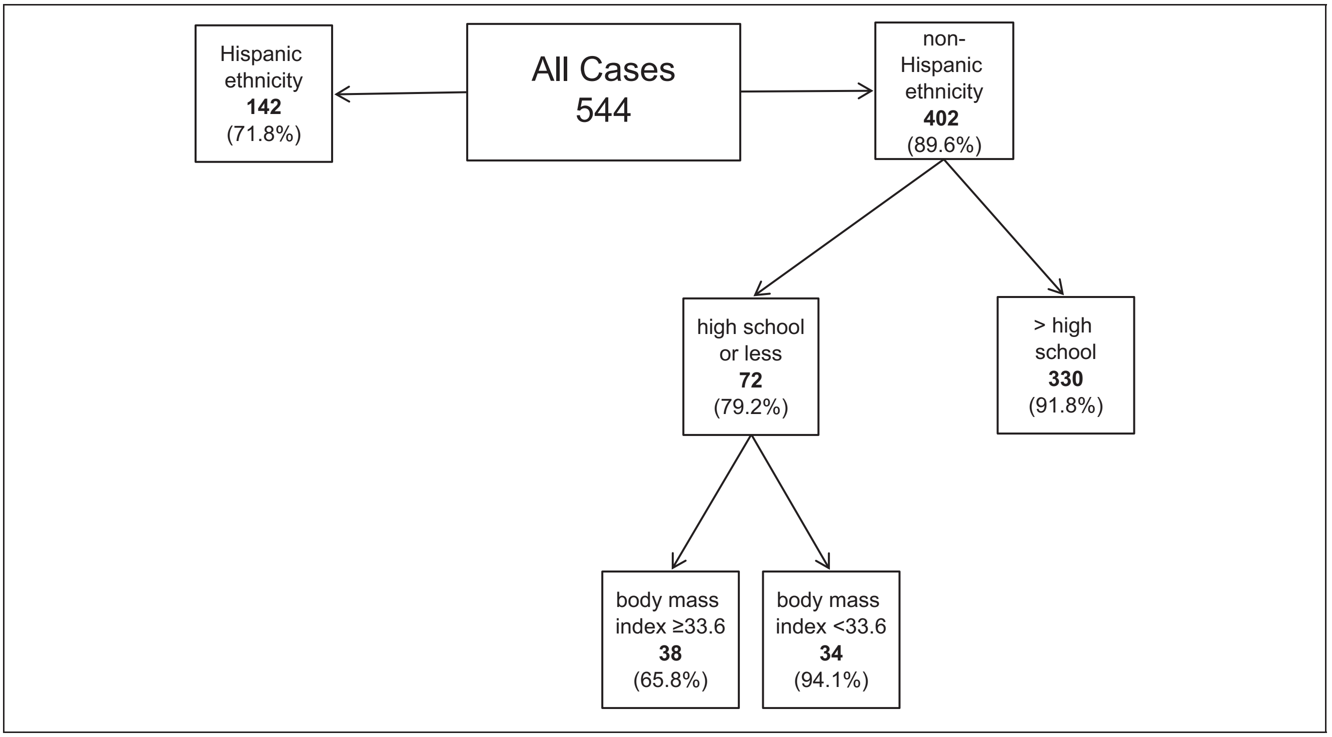

Figure 2 *Latino ethnicity, education, and body mass index were significant predictors of baseline assessment completion.*

RESULTS

Figures 1 to 5 present decision tree diagrams showing how indicator variables combined to best predict the binary outcomes for the first 5 steps of the study. No significant predictors emerged for the sixth outcome—maintenance v. nonmaintenance of behavioral gains—either in imputed or listwise signal detection analyses.

Step 1: Agree to participate (of those eligible)? Of 2076 eligible patients, 1532 (73.8%) declined participation and 544 (26.2%) agreed to take part (Figure 1). Education level, HbA1c, income, BMI, and systolic blood pressure were significant predictors of participation. In general, those with high school or less education were least likely to participate. In this group, patients with a relatively high A1c level ($\geq$7.7) had the lowest (10.8%) participation rate; those having a lower A1c level (<7.7) were more likely to participate—with a 13.5% participation rate among older patients ($\geq$56 years) and a 24.6% participation rate among younger patients (<56 years). Among more educated patients, those with greater income ($\geq$\$90,000) were more likely to participate; of these, patients with a relatively low systolic blood pressure level (<126) agreed to participate at a greater rate (65.8%) than those with a higher systolic blood pressure level. More educated patients with incomes <\$90,000 were more likely to participate if their BMI was at least 40.8 kg/m^2 compared with <40.8 kg/m^2 (41.8% v. 31.1%, respectively). Figure 1 illustrates the marked differences in agreement to participate between the highest and lowest homogeneous subgroups identified in the SDM (65.8% v. 10.8%). As with imputed data, analysis of listwise data indicated that education and income were significant predictors of participation, but smoking status also was significant (i.e., those with greater education were more likely to participate if they also were nonsmokers [66.7%] rather than smokers [48.9%]); the listwise signal detection model did not identify HbA1c, age, or systolic blood pressure as significant predictors.

Step 2: Completed baseline assessment? Of 544 patients who agreed to participate, 82 (15.1%) failed to complete baseline assessment, and 462 (84.9%) completed baseline assessment (Figure 2). Latino ethnicity, education, and BMI were significant predictors of baseline assessment completion. Latino patients had a 71.8% baseline completion rate. Among non-Latinos, baseline assessment

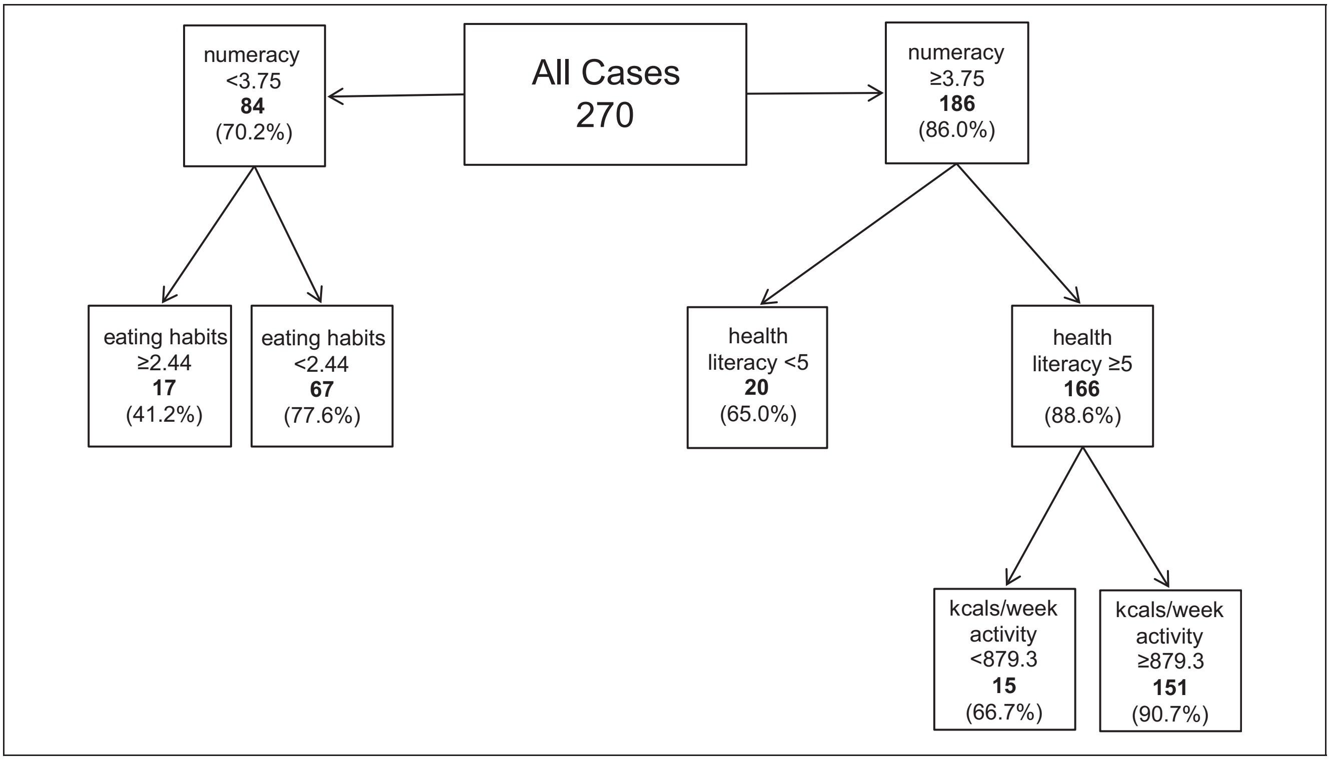

Figure 3 *Numeracy, baseline eating habits, health literacy, and baseline physical activity were significant predictors of engagement in the intervention website from baseline to 4 months.*

completion was lowest (65.8%) among those with less education (high school education or less) and a BMI value $\geq$33.6 kg/m^2; baseline completion was highest among non-Latinos who had either more than a high school education (91.8%) or less education and a BMI value <33.6 kg/m^2. SDM results were similar in analysis of listwise data, except that there was a further distinction in baseline completion rates among nonwhite v. white non-Latinos, with nonwhite non-Latinos having a 83.0% completion rate v. a 93.1% completion rate among white non-Latinos (and, among white non-Latinos, those with lower A1c values [<10.90] had a 94% completion rate compared with 77.8% of those with higher A1c values).

Step 3: Engaged in intervention website at least monthly from baseline to 4 months? Of 270 participants randomized to the 2 treatment conditions who remained in the study through the 4-month assessment, 51 (18.9%) did not visit the intervention website at least monthly and 219 (81.1%) did engage at least monthly (Figure 3). Numeracy, baseline eating habits, health literacy, and baseline physical activity were significant predictors of website visits from baseline to 4 months. Patients with higher numeracy ($\geq$3.75) generally were more engaged—with 86.0% of them visiting at least monthly compared with 70.2% in the lower numeracy group—and those with higher numeracy who also had higher health literacy ($\geq$5.00) were more engaged (88.6%) than those with lower health literacy (65.0%). The most engaged group consisted of patients with higher numeracy, higher health literacy, and higher baseline levels of physical activity—90.7% of these participants visited the website at least monthly compared with 66.7% who had higher numeracy, higher health literacy, and lower baseline physical activity. Among those with lower numeracy, patients with poorer baseline eating habits were more likely to visit the website at least monthly (77.6%) compared with those with better eating habits (41.2%). The SDM results indicated large differences between the highest v. lowest subgroups (41% v. 91%). In the listwise model, only baseline smoking status was a significant predictor of monthly website engagement, with nonsmokers being more engaged than smokers (82.5% and 64.7%, respectively).

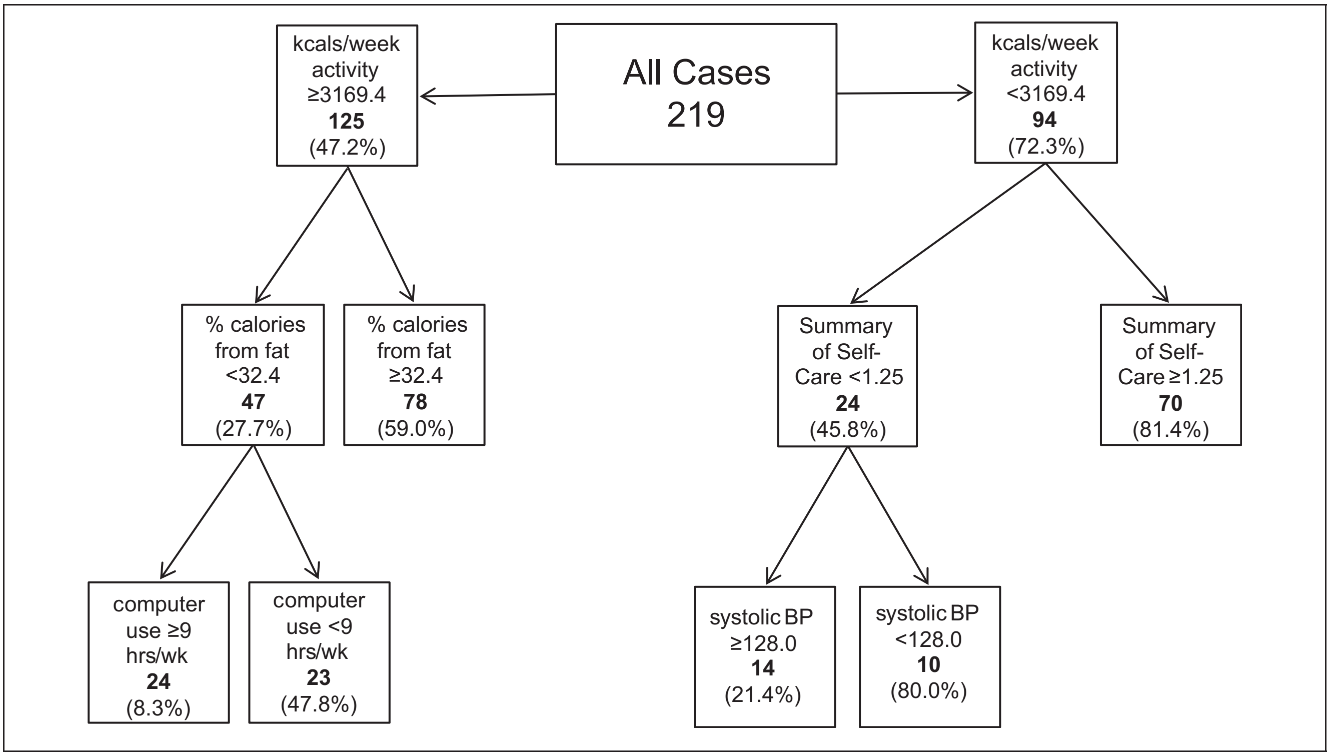

Figure 4 *Baseline physical activity, baseline fat intake, diabetes self-care activities, baseline diastolic blood pressure (BP), and baseline mean arterial pressure were significant predictors of 4-month behavioral improvements.*

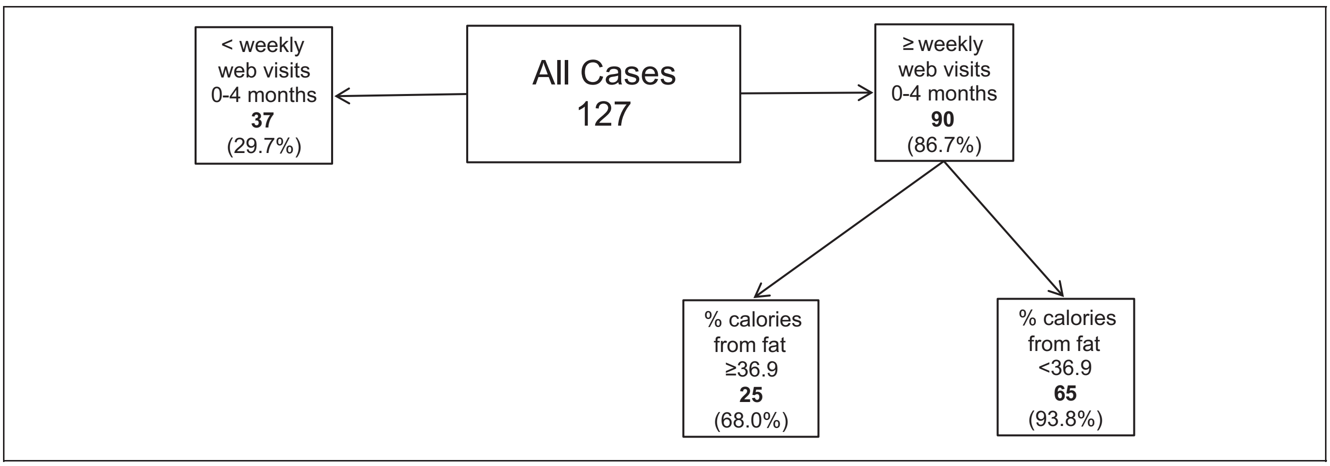

Figure 5 *Engagement at least weekly in the intervention website from baseline to 4 months and baseline fat intake were significant predictors of website visits from 5 to 12 months.*

Step 4: Improved eating and/or physical activity habits (≥50% of 1 SD) at 4 months? Of 219 intervention participants who visited the intervention website at least monthly, 92 (42.0%) did not improve physical activity and/or eating habits at 4 months, while 127 (58.0%) did improve at least 1 behavior (Figure 4). Baseline physical activity, baseline fat intake, greater baseline hours of computer usage, baseline diabetes self-care activities, and baseline systolic blood pressure were significant predictors of behavior change at 4 months. In general, the less physically active participants at baseline were more likely to improve behavior at 4 months—72.3% of those expending less than 3169 calories/wk in physical activity improved at least 1 behavior compared with 7.2% expending more calories. Among the more physically active participants, those with higher baseline fat intake were more likely to improve at least 1 behavior at 4 months relative to those eating less fat (59.0% v. 27.7%), and of those eating less fat at baseline, improvement was more likely in participants who tended to spend less time on the computer (<9 h/wk), who had a 47.8% rate of 4-month behavioral improvement compared with 8.3% among higher usage participants. Among the less physically active participants, those with better diabetes self-care were more likely to improve at least 1 behavior at 4 months. About 81.4% of those with higher self-care scores improved 4-month behavior compared with 45.8% of those with lower self-care scores. Of those in the group with lower self-care scores, participants having lower systolic blood pressure (<128.0) had a higher rate of behavioral improvement (80.0%) than those having higher systolic blood pressure (21.4%). The signal detection model with listwise data was similar but indicated that diastolic blood pressure and mean arterial pressure were significant predictors rather than systolic blood pressure.

Step 5: Engaged in website at least bimonthly during months 5–12? Of 127 participants who improved at least 1 behavior at 4 months, 38 (29.9%) did not visit the website at least bimonthly from months 5 to 12, while 89 (70.1%) did so (Figure 5). Website engagement during the first 4 months and baseline fat intake were significant predictors of website engagement in months 5 to 12. Those who had not visited the website at least weekly for the first 4 months had the lowest engagement in months 5 to 12 (29.7%). Among those who had visited the website at least weekly for the first 4 months, participants with lower baseline fat intake (<36.9% of calories from fat) had more engagement in months 5 to 12 (93.8%) compared with those who ate more fat at baseline (68.0%). Results of listwise signal detection models were similar to those conducted with imputed data.

Step 6: Maintain behavioral improvement at 12 months? Of the 89 participants who visited the intervention website at least monthly from months 5 to 12, 41 (46.1%) did not maintain 4-month behavioral improvements at 12 months, while 48 (53.9%) did sustain gains in behavior. No significant predictors of behavior maintenance emerged in either listwise or imputed data analyses.

DISCUSSION

Given the complexity and amount of data presented, and realizing that many readers are likely not used to interpreting SDM output and results, we present the following integrative summary. The factors that characterized the most successful groups varied across steps in the Internet-based DSM program. In general, demographic factors were dominant in the earlier participation/nonparticipation steps of the program but did not differentiate groups after baseline assessment. At later steps, health literacy and numeracy (for website engagement) and behavioral factors were the primary factors characterizing groups as more v. less successful. The analysis of longer term website engagement seemed to confirm the adage that ''the best predictor of future behavior is past behavior,'' which may also explain the failure to identify separate predictors of long-term behavior change maintenance at the final step. It may be that the factors predicting longer term success in this instance did not differ from those predicting initial success (and those initially less successful were not present in the later analysis to preserve independence).

The participation and baseline completion results are of concern because, despite considerable efforts to make the program culturally sensitive (e.g., having bilingual recruitment callers, having all recruitment materials and the website available in Spanish as well as English) and applicable across literacy and education levels, those less educated were less likely to participate. The strong impact of Latino ethnicity on failure to complete baseline assessment after initial agreement is also of concern and not a finding that we have found previously in our own work using linear regression models or have previously seen reported. Separating the characteristics involved in success at different steps via SDM allowed us to identify this participation issue, and it will be interesting to see whether the finding generalizes to other research.

Our primary aim was to employ SD recursive partitioning methods to address the question of who succeeds at different steps of this DSM program. In general, the approach worked well, with the exception of the final step, and produced strong separation of groups. The closest direct comparison with more traditional methods that we have is with a linear regression approach to predict participation used with this sample in an earlier publication focused on more general conceptual issues about recruitment and definitions of participation.[50] Our past Internet- and in-person–delivered intervention trials, evaluated using analyses of variance, have indicated that our programs are robust; we have found few significant demographic, medical, or behavioral differences in participants v. nonparticipants.[19,20,37] We also have found few significant associations between patient characteristics and summary website engagement variables; ethnicity, baseline computer use, age, health literacy, and education were not significantly related to website use.[20] There are multiple interpretations of this finding: it may be that demographic factors are less important at these later stages; it may be that their influence has already been removed at the earlier sequential steps; or it may be that they are confounded or colinear with other variables available at these late stages. Given that SDM and other recursive portioning methods are designed to identify homogeneous subgroups, it is not surprising that subgroups were identified, but the magnitude of the differences—sometimes as much as a 10-fold difference in success rates—is impressive. SDM has a number of conceptual strengths. It does not require linearity, is only minimally affected by multicolinearity among indicator variables, and makes few assumptions about the data. These methods have been successful in other applications also, and it may be that breaking ''success'' down into discrete steps also helps to identify patient characteristics associated with success.

This investigation has limitations. The study was conducted in a single HMO and for a single Internet-based DSM program, and the SDM approach is exploratory in nature. As with any such analysis, it will be of interest to see whether the pattern of results is replicated, especially as we did not have the sample size to conduct cross-validation analyses. In signal detection analysis of outcomes at the later steps, there were a large number of potential predictors, which is both a strength and a weakness. The $P < 0.01$ level of significance was used to compensate for the large number of comparisons—and, with the exception of the final steps, the sample sizes were larger than for most DSM studies. That said, we conducted only a subset of the possible number of subset analyses that could have been asked. We selected a priori the sequential set of steps that we felt would most inform future Internet self-management research. The finding that predictors of initial behavior change success were largely lower baseline levels on these behaviors could partially be explained by regression to the mean. Another limitation is that we did not have the resources to conduct follow-up qualitative analyses to help understand why/how the identified factors played out to influence success. Finally, we did not follow a particular theoretical model to a priori predict ''success'' but simply took all available and relevant measures for a given step and considered them as candidate predictors.

Strengths of the study include the reasonably large and moderately diverse sample, as well as the large data set that included a conceptually broad set of potential predictors and electronic health record data frequently unavailable (especially among nonparticipants) to predict initial participation. We believe the approach to analyze success at different steps—participation, engagement, initial behavior change, and longer term maintenance—in one study is also a contribution and suggests several areas for future research and practice.

Implications for research include replication of these results to determine whether the pattern of different factors being important at different steps is also true with other programs and in different settings. Like King and others,[51] who used SDM to analyze outcomes of a physical activity intervention for older adults, we found signal detection recursive partitioning methods to be helpful for understanding results of the behavioral intervention. Assuming these findings are replicated, more in-depth interviews to understand reasons for lack of success with identified subgroups could lead to important program adaptations that would address the underlying issues. We encourage others to gain experience with SDM and other recursive partitioning approaches to help explain the frequent heterogeneity of outcomes in both Internet and DSM programs.

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