A Tailoring Algorithm to Optimize Behavior Change

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Abstract

Effective computerized tailoring can enhance the impact of health interventions. Long-term success rates can be improved with prospective tailoring that builds on evidence-based research. A new algorithm, developed with data from smoking cessation clinical trials and published practice guidelines, is designed to predict the likelihood of abstinence. The algorithm prioritizes the content of a stop-smoking intervention individually for each user and indicates the potential effect of utilizing various stop-smoking medications and stop-smoking approaches. Thus, it has the potential to guide a smoker through the cessation process by dynamically optimizing the likelihood of success. Importantly, the algorithm predicts that even a daily smoker may be able to substantially improve the likelihood of quitting and staying quit both by using stop-smoking techniques and medications and by addressing emotional and cognitive issues that sustain smoking.

1. Background

1.1. Tailoring in health interventions

Applying tailoring (also called personalization or customization) to health interventions is challenging for many reasons, including the realities that health behaviors are complex and involve multiple etiologies, numerous variables, and various pathways to success. Similarly, identifying and applying effective tailoring is an exacting process because so many situations and behaviors can impact health consequences, including treatment adherence, physical activity, nutrition, management of chronic conditions, and varying levels of risk.

Tailored health interventions could enable powerful treatments to successfully help individuals and populations at risk [1]. Tailoring has been effective in diverse settings, addressing varied behaviors and populations [2-5]. Tailoring could have the potential to be a “disruptive” technique [6] that could actualize the potential of computerized interventions [7] and perhaps revolutionize health interventions.

Several factors can make tailoring more effective. A Cochrane Review [2] determined that interventions that are tailored to identify barriers to behavior change prospectively can improve outcomes. Dynamically adaptive, computer-based tailored interventions are overall more effective than single-assessment interventions [1].

Theory-based tailoring adds additional potential power to a tailoring approach. However, theory can be applied only if enough variables are explored to make theory operationalizable. Evidence indicates that theory-based interventions are more effective than those without a theoretical grounding. Also important is the use of multiple determinants (factors that influence the nature or outcome) and multiple levels of those determinants [8]. For example, high perceived stress could affect the outcome of a smoking cessation attempt. Since stress perception is scored as ordinal-level data, it can be scored at multiple levels, or in other words, is a determinant with multiple levels.

Tailoring often has been based on basic demographics and on linear criteria such as the Stages of Change (Transtheoretical Model) [9]. The Transtheoretical Model has been applied to numerous health behaviors and can be helpful in explaining why people at high risk might not be prepared to make a significant behavior change, but its linear nature does not necessarily describe the often nonlinear process of making those changes. Which is to say, while it may be instructive in defining an individual’s status, it may have limited predictive power. Although the Transtheoretical Model depicts stages in the change process in what can be a dynamic approach, it has neither multiple determinants nor multiple levels within determinants.

1.2 Computer-tailored interventions

Employing a computerized approach to tailoring allows the tailoring to be based on combinations of variables representing needs, risk factors, psychosocial factors, and biological factors. The necessary assessment and decision steps have become increasingly automated with the advent of computer-driven treatments,
but the information behind tailoring often has remained limited and nonpredictive [1].

The reasons for pursuing more effective tailoring are compelling. Computer-tailored interventions have the potential not only to provide individuals with assistance specific to their situations and preferences, but also to offer this assistance inexpensively, since large numbers of users can benefit from economies of scale. In light of the widespread—and rapidly expanding—use of mobile devices [10-11], one challenge is to improve and adapt computer-tailored interventions for innovations such as mobile platforms while taking advantage of engaging features unique to the devices.

1.3. Tailoring for smoking cessation

Smoking cessation success rates have been notoriously and abysmally low for decades, improving only with the advent of stop-smoking medications. Without some form of treatment (such as medication or counseling), only 3% to 5% of smokers who quit will remain abstinent for as long as one year [12]. With standard short-term care, only about 30% remain smoke-free. In the best of available treatment regimens, with 8-day inpatient treatment to manage withdrawal symptoms and with follow-up care, the best one-year abstinence rates are 45% to 57% [13-14].

The practice guideline for smoking cessation [15] consolidates evidence-based treatment findings and provides graded recommendations for patient treatment. This gives clinicians who have little or no background in smoking cessation a foundation for how best to help patients quit. However, it does not provide theory-based content or specific directions for tailoring. In topic areas for which research is not yet sufficiently conclusive, it is not designed to provide specific recommendations.

A tailored approach to smoking cessation interventions can help fill that gap by indicating optimal content and prioritizing content based on the individual smoker’s needs and preferences. Computerized tailoring can optimize a quit attempt by identifying and capitalizing on significant predictors of successful cessation. This highlights challenges and strengths that can affect success in quitting.

Toward that goal, the present authors analyzed data from a large cessation study to identify predictors of successful quitting in a randomized clinical smoking cessation trial [16]. Prediction of smoking relapse based on a web-based self-report survey [17] also provided insight into the predictive utility of smoking data.

In 2011-2012, the authors used data from participants in two completed clinical trials, Project EZ and COMPASS (see section 3, Methods), and from the Clinical Practice Guideline for smoking cessation [15] to devise a statistical algorithm to identify factors that could predict the likelihood of relapse, and thus could predict an individual smoker’s long-term success in quitting, given various treatment options. By modifying factors in the algorithm, the research team could see, for example, how adding a stop-smoking medication could enhance an individual’s chance of quitting successfully. The algorithm now has been operationalized and incorporated into an iPhone app, which has undergone beta testing. The goal of developing this algorithm was not to provide individuals with a likelihood-of-quitting score (which could present ethical challenges), but rather to identify areas to address with tailored content.

Applying the algorithm in a computer-based intervention, including an app, involves administering a brief questionnaire at first use of the app and repeating it in part later, to identify the smoker’s status on key factors. The tailoring algorithm then prioritizes content based on the user’s input. Tailoring prioritization changes dynamically as responses to the tailoring questions change across time. To continue to address the user’s needs, the tailoring modifies the prioritization of content throughout the quitting process, such as during a phase of relapse prevention or in the event of relapse.

2. Methods

The tailoring algorithm is based partially on two randomized clinical trials—Project EZ and COMPASS—that spanned 14 years and involved a total of 2,726 participants. The algorithm also was based on the most current Clinical Practice Guideline for smoking cessation [15]. The algorithm was operationalized by applying recommendations from the guideline and other evidence- and theory-based treatment content. (See Figure 1.)

2.1. Basis of the algorithm: Two clinical studies

Funding for Project EZ was received in 1997 from the National Cancer Institute for a clinical effectiveness trial of bupropion SR (brand name Zyban, GlaxoSmithKline, Inc.) for smoking cessation. For this open-label trial, N=1,524 adult smokers interested in quitting were randomly assigned to receive one of two doses of bupropion SR (150 mg or 300 mg) paired with minimal or moderate behavioral counseling. They were assessed for point-prevalent smoking status at 3 and 12 months. At 3 months, a significantly higher rate of nonsmoking was observed among patients who received the higher bupropion SR dose. The group receiving 300 mg and moderate counseling had a significantly higher rate of nonsmoking (35.0%) than the other treatment groups (for which nonsmoking rates ranged from 24.2% to 26.7%). At 12 months, patients receiving moderate
counseling showed a higher rate of nonsmoking (32.3%) than patients who received minimal counseling (24.6%), but the advantage previously observed for the higher bupropion SR dose was no longer apparent [18]. (See characteristics, Table 1.)

The later trial, the 2004 COMPASS study, was funded by a grant renewal to Project EZ. The study included N=1,202 adult smokers who were interested in quitting and, in addition to a study medication, were randomly assigned to one of three smoking cessation interventions: web-based counseling, proactive telephone-based counseling, or combined telephone and web counseling. Participants received a standard 12-week FDA-approved course of varenicline (brand name Chantix, Pfizer, Inc.). Intent-to-treat analyses revealed relatively high rates of abstinence for the web, telephone, and telephone + web groups, respectively, at 3 months (38.9%, 48.5%, 43.4%) and at 6 months (30.7%, 34.3%, 33.8%). The telephone-only group had significantly higher abstinence than the web group at 3 months, but no between-group differences were seen at 6 months [19]. (See characteristics, Table 1.)

2.2. Statistical development of the algorithm

For development of the tailoring algorithm, the outcome being predicted was the 6-month, 7-day point-prevalence smoking status for the N=1,202 COMPASS participants and the 12-month, 7-day point-prevalent smoking status for the N=1,524 Project EZ participants. For both studies, individuals who were nonrespondents to the follow-up surveys were coded as relapers. The relapse rates for COMPASS and Project EZ were 32.9% and 28.5%, respectively.

Variables were selected for consideration as predictors based on theory, prior literature [15], and prior analyses of these data sets [16, 18, 19]. Predictors considered in the analysis included age, cigarettes per day, number of years smoked, time to first cigarette after waking, number of previous quit attempts, whether the participant had quit smoking for at least 24 hours in the previous year, whether the participant had ever used nicotine replacement therapy, whether the participant had ever used other programs to quit (e.g., a group program, self-help smoking books, or talking with a health professional), a tobacco dependence score, whether another smoker was at the home, whether any previous quit attempt had lasted 6 months or longer, a scale for stress in the past month [22], depression history (i.e., whether the participant had ever been depressed for 2 weeks or more lifetime), body mass index, gender, and years of formal education. (See Table 2.)

For ordinal predictor variables with more than four categories, the Stata “lowess” routine was used to carry out locally weighted regression of smoking status versus each potential predictive covariate. The smoothed regression function was saved for each covariate and then visually inspected and further smoothed if it appeared to have local discrepancies that could not be explained logically. The smoothed regression function was then used as the independent variable in logistic regressions as a screen to ensure that the covariate was a significant predictor.

Potential predictors that could not be considered interval valued were treated as polytomous with separate regression coefficients for each category. Statistically significant predictors at alpha of 0.10 were then combined in a stepwise regression that also included indicator variables for different study groups, resulting in a reduced set of covariates (noted as Possible predictors in Figure 1, also listed in Table 2).

The reduced set of covariates included age, previous quit of 6 months or more, body mass index, number of cigarettes in the past 7 days at baseline, ever had lifetime depression, how soon the participant smoked after waking, years of formal schooling, stress scale score, other smoker at home, and gender.

For each covariate in the reduced set, pairwise combinations of that covariate (i.e., the “father” covariate) were generated with each other covariate; the covariates and interactions were submitted into stepwise regressions (one regression for each father covariate). This yielded 13 screened interaction terms (including five where the “father” covariate was male, and 5 where the father covariate was stress). These 13 interaction terms were entered into a stepwise regression with the reduced set of covariates at an alpha of 0.05; only a single interaction term (the interaction of stress and a previous quit attempt in the last 6 months) remained statistically significant. Two of the covariates (education and depression score) also were removed. A Receiver Operating Characteristic curve analysis using these covariates and interaction terms had an area under the curve of 0.637, with a 95% confidence interval of 0.613 to 0.661.

The algorithm was extended to include different treatments by centering all of the covariates at their mean values in the combined study population, and including constants for each treatment that yield the same average abstinence rates as those in 2008 Clinical Practice Guideline [15].
2.3. Operationalization of the algorithm

The operationalization process is described here to illustrate one way that the abstract prioritization concepts can become concrete content. This report concerns early-stage work; the application of the algorithm has not yet been tested for efficacy or effectiveness, nor has the algorithm been validated.
The researchers compiled stop-smoking concepts from the Clinical Practice Guideline [15] and from other evidence- and theory-based literature on successful cessation approaches [23-24]. These concepts then were restructured into components of the smoking cessation process to enable the development of content that could be matched to topic areas for prioritizing within the tailoring algorithm. The goals, as described here, become the smoker’s to achieve, with assistance of the stop-smoking intervention:

1. **Eliminate the smoker’s tobacco use.**
   - Subcategories: Reduce dependence level, reduce cigarettes per day to zero, gain awareness of risk to self and others, and accept the magnitude of the consequences of smoking.

2. **Manage the smoker’s environment.**
   - Subcategories: Decrease the sense of perceived stress and increase the sense of perceived control.

3. **Revise tobacco’s role in the smoker’s life.**
   - Subcategories: Understand the history and nature of tobacco use; understand tobacco as a commercial product (bring it down to size and remove its cultural meaning).

4. **Reduce automaticity of smoking behaviors.**
   - Subcategories: Recognize and respond differently to thoughts and feelings leading to lighting a cigarette; manage high-risk smoking situations, triggers, and cues; develop alternative reinforcements that replace reinforcement from smoking.

5. **Believe in the efficacy of treatment.**
   - Subcategories: Accept the conditions of cessation (withdrawal symptoms, medication side-effects, benefits of an intervention), consult health professionals regarding medications and support, and build belief that quitting will improve an ex-smoker’s quality of life.

The five categories are subsumed under primary content areas to facilitate matching content to prioritization programming. Content is coded to fit an approximate chronological position within Baker and colleagues’ [25] four phases of quitting: Motivation, Precessation, Cessation, and Maintenance. Tasks specific to the four phases are the following:

1. **Motivation:** Consider the role of tobacco in your life and your addiction; acquire or improve techniques for managing perceived stress and enhancing perceived control.

2. **Precessation:** Talk to a pharmacist and a physician or other health care professional, consider medications, set a quit date, begin to break the automaticity of smoking, prepare to quit, and build belief in the efficacy of treatment. Build a support system.

3. **Cessation:** Manage cravings, follow a medicine regimen, focus on activities beyond quitting and utilize counseling or group help.

4. **Maintenance:** Focus on feeling healthy, personal growth, staying positive, managing stressful situations, weathering negative emotions, preventing slips and relapse, and engage in life beyond smoking.

Content applicable to a pre-quit phase is coded for either the Motivation or Precessation phase, whereas relapse-prevention content is coded for either the Cessation or Maintenance phase. The researchers established a system of content-linked milestones as part of a motivational gamification strategy.

Content consists of (1) specific assignments and actions that facilitate the cessation process, and (2) a learning aspect designed to motivate, engage, and enlighten. These strategies are used in employee wellness programs [26].

### 3. Results

The goal of the algorithm is to depict the likelihood of successful cessation, given a range of intervention options from self-help to combinations of medications. The figures below (Figures 2-5) depict the algorithm-generated probabilities of becoming and remaining abstinent for tobacco in various situations.

The algorithm generates a set of probabilities that reflect the likelihood of successfully quitting, based on input of independent variables including age, tobacco dependence, quit attempt history, perceptions of stress and control, gender, body mass index, and proximity to another smoker. As those variables differ, the probability of success in quitting differs, resulting in variations in probability of successful quitting.

The figures below are based on a hypothetical case of a smoker, 25 years old, of average build, who smokes 20 cigarettes per day and is moderately tobacco dependent. Default values for these four figures are that the smoker is male, has moderate levels of perceived stress and perceived control, does not live with another smoker, and has quit smoking for at least six months at least once. As those values change in specific figures, the effect is evident in the differing levels of probability of successfully achieving long-term abstinence (defined as 6-12 months, standard duration in cessation research).

2649
Figure 2. Algorithm-calculated cessation effect of differing levels of perceived stress and perceived control. The bars show the probability of long-term abstinence using the techniques listed in the left column. Perceptions of stress and control are known to influence smoking and cessation.

Figure 3. Algorithm-calculated cessation effect of living with another smoker. The bars show the probability of long-term abstinence using the techniques listed in the left column. Having another smoker in the home affects outcome to some extent.
Figure 4. Algorithm-calculated cessation effect of having ever quit smoking for at least 6 months. The bars show the probability of long-term abstinence using the techniques listed in the left column. Smoking cessation can be viewed as a long-term learning process.

Figure 5. Algorithm-calculated cessation effect of being female or male. The bars show the probability of long-term abstinence using the techniques listed in the left column. Gender can effect smoking cessation outcomes, more negatively for females than for males.
4. Discussion

A current limitation of the tailoring algorithm is that, at present, it is based only on variables included in the two clinical studies and the practice guideline. If the database driving the algorithm is expanded over time with additional results and additional measures, the algorithm has the potential to become more predictive and therefore more effective. Additionally, the demographics of the two clinical studies incorporated into the algorithm differ from those of the average U.S. smoker, particularly on racial/ethnic dimensions.

The limitation of the current operationalization of the algorithm is that it has not yet been examined for efficacy or effectiveness.

4.1. Importance of addressing health behaviors

At a time when U.S. health care costs continue to escalate and available health care funds decline [27], inexpensive and effective interventions are welcomed by patients and providers alike. Addressing health issues that have pressing repercussions, such as tobacco use, is imperative both because of the rates of death and disease attributable to preventable causes [28] and because many affected persons, such as smokers, are actively looking for help [29].

Enabling the potential of mobile technology to address these conditions will rely on the computing power and connectivity of mobile devices. With smartphones now in the majority of U.S. households [10] and tablets in one-third of households [11], mobile applications increasingly have the potential to revolutionize the interface between healthcare providers and patients, to deliver personalized medicine effectively and immediately, and to help users manage their health and wellness. Even without smartphones and tablets, some mobile interventions show promise with just the use of SMS texting [32].

Smoking is both a justifiable starting place and a suitable launching pad for studying the potential impact of a unique algorithm designed to optimize success in behavior change. Smoking remains the single greatest cause of preventable death and disease in the United States, contributing to more than 400,000 U.S. deaths annually and far outweighing all other causes of preventable death and disease [33].

4.2. Future directions

Several substantial steps remain before the algorithm will be considered fully developed, beyond some currently planned development and programming enhancements to the app that uses the algorithm:

1. Development of any application of the algorithm must ensure the quality of the user experience.
2. The efficacy and effectiveness of an intervention that utilizes the existing algorithm should be established. This will help validate the algorithm approach.
3. As additional clinical data can be incorporated, the smoking-related variables available for the algorithm can be expanded, increasing the predictive capacity of the algorithm.
4. The algorithm can be programmed so that its tailoring becomes increasingly accurate and specific as increasing numbers of participants use the algorithm in cessation interventions and provide usage and outcome data.
5. The algorithm can be more widely applicable with broader demographic representation, so that it more closely matches the demographics of populations at risk (e.g., users of other types of tobacco, or groups with high smoking rates and low cessation rates) as well as the overall population of U.S. smokers.
6. Tailoring algorithms can be developed for other risky health behaviors, through collaboration with researchers with rich datasets comparable to those used to develop the smoking algorithm.

5. Conclusion

Considerable work remains before an algorithm-based intervention can reify and demonstrate the potential of the algorithm approach. This report represents the initial steps toward that end.

Limitations and preliminary nature notwithstanding, it is important to recognize that this initial algorithm effort does depict the clinical reality of smoking cessation. An optimistic interpretation of the algorithm’s initial results is this: The algorithm predicts that even a daily smoker may be able to substantially improve the likelihood of quitting and staying quit by using stop-smoking techniques and medications, and by addressing emotional and cognitive issues that sustain smoking.

Acknowledgments

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Table 1. Baseline characteristics of participants in Project EZ and COMPASS.

<table>
<thead>
<tr>
<th>Characteristic</th>
<th>Project EZ N=1,524</th>
<th>COMPASS N=1,161</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (SD) or %</td>
<td>Mean (SD) or %</td>
</tr>
<tr>
<td><strong>Demographics</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age (years)</td>
<td>45.1 (11.8)</td>
<td>47.3 (10.9)</td>
</tr>
<tr>
<td>Gender (% female)</td>
<td>57.4%</td>
<td>66.8</td>
</tr>
<tr>
<td>Race (% white)</td>
<td>89.7%</td>
<td>89.6</td>
</tr>
<tr>
<td>Years of formal schooling</td>
<td>13.7 (2.0)</td>
<td>14.1 (2.2)</td>
</tr>
<tr>
<td>Marital status (% married)</td>
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<tr>
<td>Level of education</td>
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<tr>
<td>Less than high school</td>
<td>3.9%</td>
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</tr>
<tr>
<td>High school graduate</td>
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<tr>
<td>Some after high school</td>
<td>40.1%</td>
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</tr>
<tr>
<td>College graduate</td>
<td>22.2%</td>
<td></td>
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<tr>
<td><strong>Tobacco use and exposure</strong></td>
<td></td>
<td></td>
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<tr>
<td>Cigarettes per day</td>
<td>23 (9.8)</td>
<td>19.7 (8.1)</td>
</tr>
<tr>
<td>Years smoked</td>
<td>26.5 (11.9)</td>
<td>27.6 (11.4)</td>
</tr>
<tr>
<td>Dependence score*</td>
<td>5.8 (2.1)</td>
<td>5.0 (2.1)</td>
</tr>
<tr>
<td>Other smokers in household* (%yes)</td>
<td>44.6%</td>
<td>44.3%</td>
</tr>
<tr>
<td><strong>Quitting history</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of previous quit attempts</td>
<td>5.9 (10.0)</td>
<td>9.3 (14.8)</td>
</tr>
<tr>
<td>Previous use of nicotine patch or gum (% yes)</td>
<td>66.3%</td>
<td>83.0%</td>
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<tr>
<td>Quit attempt in previous year (% yes)</td>
<td>44.8%</td>
<td>48.2%</td>
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<tr>
<td>Previous quit attempt of at least 6 months (% yes)</td>
<td>31.0%</td>
<td>36.5%</td>
</tr>
<tr>
<td>Previous use of bupropion (% yes)</td>
<td></td>
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Table 2. Items included in algorithm development.

<table>
<thead>
<tr>
<th>Items from Project EZ and COMPASS used in algorithm development</th>
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<tbody>
<tr>
<td>Age</td>
</tr>
<tr>
<td>Gender</td>
</tr>
<tr>
<td>Body Mass Index</td>
</tr>
<tr>
<td>Cigarettes/day in previous 7 days</td>
</tr>
<tr>
<td>Number of years smoked regularly</td>
</tr>
<tr>
<td>Time to first cigarette after waking</td>
</tr>
<tr>
<td>Tobacco dependence scale</td>
</tr>
<tr>
<td>Live with another smoker</td>
</tr>
<tr>
<td>Quit for at least 24 hours in previous year</td>
</tr>
<tr>
<td>Ever quit for at least six months</td>
</tr>
<tr>
<td>Ever tried nicotine patch or gum</td>
</tr>
<tr>
<td>Ever use cessation support</td>
</tr>
<tr>
<td>Feel that things are going your way</td>
</tr>
<tr>
<td>Feel unable to control things</td>
</tr>
<tr>
<td>Feel confident in ability to handle problems</td>
</tr>
<tr>
<td>Feel unable to control important things</td>
</tr>
<tr>
<td>Feel low energy or slowed down</td>
</tr>
<tr>
<td>Ever sad, blue, depressed, lost interest for ≥ 2 weeks</td>
</tr>
<tr>
<td>Years of formal schooling</td>
</tr>
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</table>

2653
References


