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Editorial Open Access

Dynamic Baseline Variables Predict Treatment Outcomes for Addiction Generally, and Smoking in Particular

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Editorial

Despite their importance in treatment outcomes and utility in message framing and treatment engagement, demographic variables are not reliable predictors of treatment outcomes for smoking cessation. In analyzing treatment outcomes across five studies, Velicer, Redding, Sun & Prochaska [1] found no significant differences across gender, race and ethnicity for smoking cessation, although they did find a few significant, though small, effects for age and education subgroups. With effect sizes near zero for race and small effect sizes for ethnicity, they concluded that tailored behavioral intervention is about equally effective across racial and ethnic subgroups. Since then, in analyzing treatment outcomes among smokers, Redding et al. [2] also did not find significant differences across demographic variables. These data lend additional support to the Center for Disease Control's [3] earlier report which concluded that smoking cessation interventions are generally of similar effectiveness for men and women, and that few gender differences have been identified. Given these findings, and the fact that smoking remains one of the top causes of preventable deaths in the U.S. [4], Borrelli [5] concluded that smoking cessation interventions have reached an asymptote and called for more thoughtfully conducted a priori definitions, criteria and standardized processes in order to jump-start stalled smoking cessation rates.

Although research has shown that baseline demographic variables are not predictive of treatment outcomes, research has revealed that dynamic baseline variables do predict outcomes. A common dynamic baseline variable in addiction research and treatment is problem severity. For smoking cessation specifically, a common measure of problem severity is the time to a smoker's first cigarette of the day. This dynamic variable, as well as several other indicators of problem severity, is measured by the Fagerstrom Index [6]. Analyzing problem severity and demographic variables among smokers, Falba, Jofre-Bonet, Busch, Duchovney & Sindalar [7] found problem severity was inversely related to success across demographic variables. Since then, Redding et al. [2] found significant small-to-medium-sized differences between stable smokers and those who relapse following cessation based on the dynamic baseline variables of problem severity, stages of change (SOC) and effort, although no differences were found among demographic variables. These data provide additional support to Sheeran's [8] earlier meta-analysis which concluded that dynamic baseline variables (i.e., intention to change/SOC), unlike demographic variables (i.e., race, gender, ethnicity), are essential to promoting treatment outcomes. Another important finding in this meta-analysis is that intention alone was insufficient to predict treatment outcome as only 47% of those with positive intention to take Action (i.e., successful treatment outcome) actually did take Action. Overall, these data suggest that demographic variables are "static" in that they cannot be changed by treatment, whereas dynamic variables can be. Although dynamic baseline variables such as problem severity and intention to change/SOC are reliable baseline predictors of treatment outcomes, research and treatments need a new direction.

Multiple behavior change is a small but rapidly growing area of clinical research considered by some to be the future of prevention research [9]. Investigating treatment outcomes that simultaneously intervene on multiple behavior risks, multiple behavior change may be of particular importance for smokers and stalled smoking cessation rates. For example, among tobacco users, it is estimated that approximately 92% also meet criteria for at least one additional risk behavior such as heavy alcohol drinking, physical inactivity, or low consumption of fruits and vegetables [10,11]. In analyzing multiple health behavior change for smoking, diet, and unprotected sun exposure, Blissmer et al. [12] found that although baseline demographic variables did not predict treatment outcomes, and that they had the smallest effect sizes, the baseline dynamic variables of decisional balance, processes of change and self-efficacy did. Since then, when investigating a pooled data analysis of three trials including smoking cessation, Paiva et al. [13] found that individuals who made a behavior change (i.e., quit smoking) were more likely to make similar progress on another targeted behavior compared to those individuals who did not make a behavior change. Additional data further reveal that smokers who make progress toward smoking cessation are more likely to make treatment progress on another risk behavior compared to smokers who do not make treatment progress toward smoking cessation [14]. Considered together, treatment outcomes for both single behavior change and multiple behavior change targeting smoking cessation consistently reveal that dynamic baseline variables are the best predictors of outcomes.

The importance of dynamic variables, particularly during the initial phase of health interventions [1], provides empirical evidence to examine the interrelationships of dynamic baseline variables in smoking cessation treatment outcomes. In doing so, we may be able to jump-start stalled smoking cessation rates, address the fact that smoking remains among the most pressing health issues in the U.S. and provide a direction for future research and treatment in addictions [15-16].

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