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Preliminary Evidence of Contextual Factors' Influence on Weight Loss Treatment Outcomes: Implications for Future Research

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Abstract

Background/Objectives: Behavioral health interventions, including behavioral obesity treatment, typically target psychosocial qualities of the individual (e.g., knowledge, self-efficacy) that are largely treated as persistent, over momentary contextual factors (e.g., affect, environmental conditions). The variance in treatment outcomes that can be attributable to these two sources is rarely quantified but may help inform future research and treatment development efforts.

Subjects/Methods: The intraclass correlation coefficient (ICC) for weekly weight loss was calculated in three studies involving 10–12 weeks of behavioral obesity treatment delivered to adults via in-person group sessions, mobile application, or website. The ICC explains the proportion of variance between versus within individuals, and was used to infer the contribution of individual versus contextual factors to weekly weight loss. The analytic approach involved unconditional linear mixed effect models with a random effect for subject.

Results: The ICCs were very low, ranging from 0.01 to 0.06, suggesting that momentary contextual factors may influence obesity treatment outcomes to a substantial degree.

Conclusions: This study yielded preliminary evidence that the influence of contextual factors in behavioral obesity treatment may be underappreciated. Future research is needed to simultaneously identify and quantify sources of within- and between-subjects variance to optimize treatment approaches.

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Dr. Thomas's has received compensation as a member of the scientific advisory board of Lummé Health and owns stock in the company. Dr. Goldstein and Dr. Brick declare no potential competing interests.

INTRODUCTION

The theoretical frameworks that serve as the foundation of most evidence-based behavioral health interventions, including those that target body weight and related behaviors, often focus on psychosocial constructs as important determinants of behavior. For example, knowledge, self-efficacy, behavioral intentions, outcome expectancies, normative beliefs, social support, and stage of change are key psychosocial aspects of the theoretical frameworks that have heavily influenced behavioral obesity treatment, such as Social Cognitive Theory,[1] Self-regulation Theory,[2] the Theory of Planned Behavior,[3] Cognitive Behavioral Therapy,[4] and the Transtheoretical Model.[5] These psychosocial constructs are often conceptualized as modifiable qualities of an individual, and because they are assumed to be major drivers of behavior, they are primary targets of treatment.

While theoretical frameworks do not necessary conceptualize psychosocial qualities of the individual as trait-like, they are often treated as such in research and clinical contexts, perhaps due to how they are measured (e.g., only 2–3 times throughout a study, often via questionnaire) and intervened upon (i.e., infrequently, often via occasional clinic visits). Thus, in practice, most evidence-based behavioral obesity treatments attempt to produce health behavior change by modifying psychosocial qualities of an individual that are treated as largely persistent (i.e., trait-like), with less attention paid to the impact of context (e.g., environmental conditions and experiences in the moment).[6]

Despite the relative success of behavioral obesity treatment and findings that highlight psychosocial targets as mechanisms for treatment outcomes, the assumed impact of theory-based psychosocial qualities of the individual is not always born out.[7] The variance in outcomes of interventions targeting weight loss is often very large with psychosocial characteristics (typically analyzed as between-subjects effects) explaining a relatively small proportion of it.[8–10] Recent reports have highlighted the importance of considering both between- and within-subjects effects on health behaviors, indicating the drawbacks of assuming that persistent psychosocial qualities of the individual are stable across individuals without also accounting for other momentary contextual factors (e.g., affect, stress, environmental conditions, moment-to-moment variations in psychosocial qualities within persons; typically analyzed as within-subjects effects).[11,12] Thus, factors other than the targeted psychosocial qualities of the individual may exert a substantial effect on weight-related behaviors and outcomes of behavioral obesity treatment, but this idea is rarely tested.

This brief report explores one potential indicator of the degree to which behavioral obesity treatment outcomes are the result of persistent characteristics of the individual versus contextual influences: the intraclass correlation coefficient (ICC) of weekly weight change. The ICC represents a correlation of observations within an individual that can range from zero to one.[13] Hypothetically, if persistent (e.g., trait-like) psychosocial qualities of the individual are more responsible for treatment outcomes, then the ICC might trend closer to one (i.e., the variance in weekly weight change across treatment is primarily attributable to between-subjects factors, such that some individuals with greater strengths and/or fewer vulnerabilities consistently lose more weight than others). If contextual factors exert a strong influence on treatment outcomes, the ICC might trend closer to zero (i.e., the variance in weekly weight change across treatment is primarily attributable to within-subjects factors, such that all patients have a wide range of week-to-week weight loss, with little consistency in who has more "good" versus "bad" weeks). This preliminary investigation of weekly weight change compares the ICCs across three modalities of behavioral obesity treatment: group sessions, mobile application ('app'), and automated online treatment.

MATERIALS/SUBJECTS AND METHODS

Weekly weight change was computed in three previously published studies involving 10–12 weeks of weight loss treatment using baseline weight as a reference point (i.e., $(\text{Weight}_{Week\ 2} - \text{Weight}_{Week\ 3})/\text{Weight}_{Baseline}$). Weight was measured weekly in the clinic in the group treatment arm of the Live SMART trial (weekly weights were not available in the smartphone or control conditions), in which 106 adult participants (82.1% women, 94.3% Non-Hispanic White, baseline BMI= 35.2 kg/m^2) attended 9.4 (SD=2.3) of 12 possible clinic visits during the initial 12 weeks of treatment.[14] Weight was measured weekly via Bluetooth scales in the OnTrack trial; 116 adult participants (83.6% women, 69.8% Non-Hispanic White, baseline BMI= 34.6 kg/m^2) who used mobile apps for weight loss completed 7.4 (SD=2.9) of 10 self-weigh-ins during the 10-week treatment.[15] Participants in the active intervention arm of the Rx Weight Loss trial, involving automated online behavioral weight loss treatment provided to 77 adults (80.5% women, 84.4% Non-Hispanic White, baseline BMI= 34.9 kg/m^2) referred by primary care physicians, recorded their weight an average of 10.3 (SD=3.1) weeks during the 12-week treatment.[16] Study protocols were approved by the Institutional Review Boards of The Miriam Hospital and Drexel University. Informed consent was obtained from all study participants.

Statistical Approach

Three separate unconditional linear mixed effects models were used to assess the variance in weekly weight loss and to calculate the ICC of weekly weight change in each study. An AR(1) correlation structure was used to account for greater correlations between week-to-week weight losses. Analyses were repeated using week of treatment as a fixed effect, to account for the possible slowing of weight loss over time, which could contribute to within-subjects variability. All available data were included in the analyses; maximum-likelihood estimation was used to account for missing data.

RESULTS

See Table 1 for variance components estimates across studies. The ICC of weekly weight change was .03 in the Live SMART trial, .04 in the OnTrack trial, and .01 in the Rx Weight Loss trial. ICCs were slightly higher when accounting for the effect of time (.06 for Live SMART, .05 for OnTrack, and .05 for Rx Weight Loss). These values indicate that 1–6% of the variability in weekly weight loss can be attributed to subject-level individual difference factors such as psychosocial qualities of the individual. The remainder can be attributed to contextual factors that change from week to week.

DISCUSSION

Across three studies of behavioral obesity treatment that varied in delivery modality (in-person group, mobile app, website), ICCs were uniformly very low, ranging from 0.01 to 0.04, even when accounting for slowing of weight loss over time (0.05 to 0.06). Results indicate that weekly weight losses were highly variable within individuals. Thus, the influence of contextual factors (e.g., changing environmental conditions, experiences in the moment) on obesity treatment outcomes may be stronger than is typically assumed. These contextual factors represent a promising candidate for understanding the large variability in weight change during behavioral obesity treatment.

There are several potential explanations for the low ICCs observed in this study. Psychosocial treatment targets (knowledge, self-efficacy, behavioral intentions, etc.) may not be as strong an influence on behavior as previously assumed. Alternatively, psychosocial factors may be highly influential, but prevailing assessment methods may not adequately capture the variability in the constructs and their time-varying associations with weight loss. Or, it may be that other momentary contextual factors exert a more powerful influence than previous research has been able to detect. Some research has already demonstrated that contextual factors, including affect, stress, and environment (e.g., access to food), can impact weight-related behaviors like diet and exercise. For example, one study revealed that contextual influences, combined with baseline factors (e.g., sex, age, BMI), can be utilized with machine learning to predict dietary adherence in behavioral obesity treatment with 72% accuracy.[17] This study, among others,[18] elucidates how momentary contextual factors might influence momentary adherence, and subsequently short-term weight change.

Considerable research has focused on measuring between-subjects predictors of long-term weight change,[7–10] but more work like that of Goldstein et al. is needed to identify within-subjects predictors of short-term weight change,[17] which an ICC alone cannot elucidate. Real-time intensive longitudinal assessment methods, including wearable devices and ecological momentary assessment (a method for measuring behaviors, experiences, and environmental conditions in near-real-time), are especially suited for this purpose.[19] The increased variability captured via real-time assessment may help explain within-subjects variation and subsequently inform updates to theoretical frameworks and their utilization that incorporate a greater role of contextual influences. If supported, the role of contextual factors may further enable personalized treatment strategies such as just-in-time adaptive intervention (JITAI) that involve selecting and delivering treatment based in part on factors measured moment-to-moment.[20]

This study has strengths including calculation of an ICC across several studies that varied in intervention delivery modality and assessment methods. Additionally, while the target of many behavioral health interventions is subjective, body weight is easily measured objectively. There are also limitations, in addition to those noted above, that should be considered. We did not account for well-known between-subjects differences that are consistently related to weight loss (e.g., men tend to lose more weight). However, our goal was not to explain between-subjects variance but rather highlight within-individual variations in weekly weight loss. Our analytic approach assumes that missing data are

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missing at random (MAR), but participants may have been less likely to complete weigh-ins when weight loss was poor, or weight gain had occurred. Finally, the ICC of weight loss during behavioral obesity treatment may change depending on the time frame being considered (e.g., weekly vs. monthly weight change). For example, the ICC in our studies may be low because there are limits to the amount of weight that can be lost in a single week (vs. a month or a year) which, in turn, limits the variability in between-subjects weekly weight loss.

To our knowledge, this is the first time that the ICC of weekly weight loss has been examined across obesity treatment trials. It appears that the longitudinal between- versus within-subjects variability in change in outcomes over a treatment period is rarely analyzed in randomized trials in behavioral medicine, more broadly. We encourage investigators to design and analyze their studies in such a way that the analysis described herein can be replicated. It may be possible to do so with other completed trials, as we have done. Our study also suggests that future research aimed at identifying *sources* of both between and within subjects variance, simultaneously, will be particularly important for optimizing behavioral obesity treatment and its outcomes.

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Table 1.

Variance components and intraclass correlation coefficient (ICC) from generalized linear mixed models of weekly weight change in three studies of behavioral obesity treatment.

Unconditional Models (Random Effect of Subject Only)			
Study	Subject-level Variance	Residual Variance	ICC
Live SMART Trial[14]	0.03	0.91	0.03
OnTrack Trial[15]	0.04	1.03	0.04
Rx Weight Loss Trial[16]	0.01	1.03	0.01

Conditional Models (Fixed Effect of Time and Random Effect of Subject)			
Study	Subject-level Variance	Residual Variance	ICC
Live SMART Trial[14]	0.05	0.82	0.06
OnTrack Trial[15]	0.05	0.95	0.05
Rx Weight Loss Trial[16]	0.04	0.85	0.05

Subject level variance represents an estimate of the variance attributable to between-subjects factors (e.g., individual differences). Residual variance represents an estimate of the variance attributable to other sournces (e.g., contextual factors). The ICC is a ratio of subject-level variance and total variance (subject level-variance and residual variance).