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Optimizing Eating Disorder Treatment Outcomes for Individuals Identified Via Screening: An Idea Worth Researching

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Abstract

In recent years, online screens have been commonly used to identify individuals who may have eating disorders, many of whom may be interested in treatment. We describe a new empirical approach that takes advantage of current evidence on empirically-supported, effective treatments, while at the same time, uses modern statistical frameworks and experimental designs, data-driven

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science, and user-centered design methods to study ways to expand the reach of programs, enhance our understanding of what works for whom, and improve outcomes, overall and in subpopulations. The research would focus on individuals with eating disorders identified through screening and would use continuously monitored data, and interactions of interventions/approaches to optimize reach, uptake, engagement, and outcome. Outcome would be assessed at the population, rather than individual level. The idea worth researching is to determine if an optimization outcome model produces significantly higher rates of clinical improvement at a population level than do current approaches, in which traditional interventions are only offered to the few people who are interested in and able to access them.

Keywords

eating disorders; screening; reach; uptake; engagement; outcome; digital technologies

In recent years, online screens have been used to identify individuals at risk for or with subthreshold/threshold eating disorders (EDs), with the intention of motivating individuals with EDs to consider treatment (Fitzsimmons-Craft, Balantekin, Graham, et al., 2019). Routine online screening through organizations such as the National Eating Disorders Association (NEDA), Mental Health America, and the Healthy Minds Network have identified hundreds of thousands of individuals at risk for or with EDs who are not receiving care (Eisenberg, Hunt, Speer, & Zivin, 2011; Fitzsimmons-Craft, Balantekin, Graham, et al., 2019).

Despite the successes in identifying individuals with EDs in need of intervention, gaps remain in optimizing outcomes for these individuals: (1) screens do not reach all of those in need; (2) there is a large treatment gap between the number of individuals in need of and who receive treatment for an eating disorder (Hart, Granillo, Jorm, & Paxton, 2011); (3) the number of individuals who follow through on treatment recommendations after a screen is suboptimal (DeBar et al., 2009); and (4) among those who do receive treatment, many individuals fail to complete a full course of treatment or achieve a desired outcome within a set timeframe (Bauer & Moessner, 2013; Eisenberg et al., 2011; Fitzsimmons-Craft, Balantekin, Eichen, et al., 2019; Fitzsimmons-Craft, Balantekin, Graham, et al., 2019; Fitzsimmons-Craft, Eichen, et al., 2019; Fitzsimmons-Craft, Firebaugh, et al., 2019; Kazdin, Fitzsimmons-Craft, & Wilfley, 2017; Lindenberg, Moessner, Harney, McLaughlin, & Bauer, 2011).

The rise of digital technology, analytic methods of big data, and a variety of intervention modalities create a timely opportunity—if not urgent need—to study how effective, accessible, affordable interventions can be made available and attractive to the large numbers of individuals identified through online screening as having an ED and who may be interested in treatment. In this *Idea Worth Researching*, we argue for optimizing ED treatment through research that evaluates and subsequently manipulates factors that individually and collectively impact health outcomes: screening reach, intervention uptake, and intervention engagement. Although we focus on patient-level factors, reducing the treatment gap also requires addressing provider and health care system factors, such as

reducing barriers affecting service delivery (e.g., insurance reimbursement (Whiteford & Weissman, 2017)). Further, some providers fail to detect an ED even when potential patients present for ED treatment (Cachelin, Rebeck, Veisel, & Striegel-Moore, 2001) as would be the case if they were self-referred by a screen, and studies of electronic health records suggest that EDs may be undertreated in regards to type of treatment (e.g., the low percentage of individuals with anorexia nervosa who received in-patient treatment Striegel-Moore, Leslie, Petrill, Garvin, & Rosenheck, 2000).

Improving Screen Reach

Reach, for this paper, is defined as the number of individuals with EDs in a population who complete a screen. Reach can be impacted by factors such as the screen advertisement methods, screen content and design, mental health literacy, need for parental consent, and access issues depending on the mode of delivery.. In traditional intervention studies, recruitment strategies usually reach populations already motivated for intervention, resulting in a potentially biased and select sample relative to the population in need of services (Mohr, Weingardt, Reddy, & Schueller, 2017). Relatively little data exists on intervention effectiveness when implemented with more general populations or in groups not often included in traditional studies.

Improving screen reach through optimization would entail iteratively designing and testing different strategies to increase the number of individuals with EDs who complete screening within the population. To begin, a research team would establish an “optimization criterion” (i.e., target) that meets an implementation goal and/or is based on, and ideally exceeds, previous reach rates. For example, research on university campuses has generally shown that <6% of students complete online screening when more traditional recruitment methods are utilized (e.g., flyers, email) (Fitzsimmons-Craft, Karam, Monterubio, Taylor, & Wilfley, In press). Then, the team would systematically manipulate recruitment strategies to determine which strategy or collection of strategies achieves the optimization criterion. As strategies are identified that achieve the optimization criterion, the team could iteratively increase the target reach rate.

Improving Intervention Uptake

Uptake refers to how many individuals offered an intervention actually begin it (e.g., open the first screen of a guided self-help intervention, make an appointment to see a provider). Uptake can be influenced by such factors as personalization of screening feedback and/or recommendations, features associated with the intervention options themselves (e.g., accessibility, cost, time-commitment, intervention content, and type such as self-guided, coached, blended, or face-to-face), and user motivation/readiness for change or perception of need.

To improve uptake, a research team would identify the optimization criterion. For instance, Fitzsimmons-Craft, Firebaugh, et al. (2019) found 50% uptake of digital programs among a university sample following an online screen; surpassing this number could be the target. Then, strategies would be tested that address factors impacting uptake, like varying the type

of feedback users receive following screening. For instance, the team could randomly assign respondents to one of three conditions: provide simple feedback, interactive feedback that aligns treatment options to user interests, or feedback that uses interactivity to enhance motivation strategies. The condition that yields the highest uptake would be implemented for all users in the next iteration. Of note, uptake also needs to consider available resources and other systemic factors (Whiteford & Weissman, 2017).

Improving Intervention Engagement

Engagement refers to how much and which parts of the intervention are used. For digital interventions, as well as traditional therapy, drop-out is a major problem. Engagement can be influenced by accessibility, perceived fit, time-commitment, helpfulness, usability, and availability of alternative options. Like the other parameters, the goal of optimization would be testing intervention variations that improve engagement beyond previously achieved rates (e.g., Andersson, Titov, Dear, Rozental, & Carlbring, 2019; Yardley et al., 2016).

Improving Intervention Outcome

The ultimate goal of a defined population intervention is to increase the number of individuals in the population who achieve a clinically-significant outcome, defined as a significant reduction in clinical symptoms or loss of caseness based on pre-specified criteria (e.g., from clinical studies). When a new optimization system is rolled out, the first deployment may provide baseline outcome data, upon which future iterations would work to improve. Inherent to the outcome optimization model is using modern statistical designs to rapidly and efficiently increase effect sizes, overall and for subpopulations. However, the emphasis should not be on improving the efficacy of only one type of intervention, but on considering population needs and interests, costs, and other factors from which to employ a suite of interventions and perhaps even sequencing strategies (e.g., stepped care models) to improve outcomes for the defined population of interest (Wilfley, Agras, & Taylor, 2013). As an example, data from NEDA suggest there are large numbers of individuals with EDs in rural and remote areas who are unlikely to have access to ED (let alone evidence-based) treatment (Fitzsimmons-Craft, Balantekin, Graham, et al., 2019; Figure 1). A defined population strategy might thus develop and evaluate ED teletherapy interventions for rural populations. As another example, personalization can occur through analyses of moderators, mediators, and personal choices to generate an array of interventions; new research models that enable examining variations in the personalization of intervention delivery are needed to help determine which are effective.

However, a challenge is assessing patients' intervention retention and outcomes. Like other factors, different strategies to increase outcomes could be tried, for instance, requiring providers who receive referrals to report de-identified outcome data, encouraging screen completers to join a research outcome monitoring project, or using information science to identify improvement unobtrusively.

Putting it All Together

Each of the aforementioned parameters—reach, uptake, engagement—influence health outcomes, which subsequently contribute to the overall individual impact of interventions (Glasgow, Klesges, Dzewaltowski, Estabrooks, & Vogt, 2006). These parameters can be monitored and tweaked individually. However, to further innovation and the speed at which we translate discovery into implementation, an ideal approach entails monitoring and iterating on these parameters simultaneously and/or sequentially within an optimization model across a population. This is important because changing one parameter likely affects other parameters, requiring considerations of tradeoffs. For instance, a strategy may be successful at reaching an underserved population that has not been heavily represented in clinical trials, but the intervention may not have been optimally designed for that population and the effect is unknown. Increasing reach also may yield more but less motivated individuals with the effect of decreased uptake. Thus, increasing reach may subsequently require iteratively identifying strategies that ensure optimal engagement and outcomes. However, increasing the reach of an intervention (assuming the same efficacy across the expanded population) may lead to clinical improvement in more people than would increasing efficacy of that same intervention (Moessner & Bauer, 2017). As another example of trade-offs, shortening an online intervention might increase engagement and reduce dropout but decrease individual effectiveness. Indeed, the outcome optimization process is dynamic and should comprise frequent changes based on continuously evaluating data from relevant parameters to maximize optimization.

In summary, we believe that reach, uptake, engagement, and outcomes can be best studied from a population-based framework that focuses on optimizing outcomes overall and for subpopulations. To achieve this goal, modern research methods and models can be leveraged, such as statistical, data-driven scientific frameworks, experimental designs, and user-centered design methods, to study ways to expand reach while enhancing our understanding of what works for whom and improving outcomes (e.g., Brown et al., 2017; Collins, 2018; Collins, Murphy, & Strecher, 2007; Graham et al., 2019; Mohr, Lyon, Lattie, Reddy, & Schueller, 2017). For example, the Multiphase Optimization Strategy (Collins, 2018) provides a framework for optimizing an intervention based on an optimization criterion. Similarly, an outcome optimization model like we are proposing would specify criteria for optimizing the full spectrum of care from screening to outcome. Parameters can be iterated upon individually or simultaneously, depending on the research goals and study designs chosen. A variety of study designs and methodologies could be used, including traditional studies, descriptive/qualitative research (e.g., determining personalization strategies using user-centered design methods (Graham et al., 2019)), and information science methodologies (to predict outcomes, e.g. from user search histories or text messages, before obtaining outcome data), examined in a variety of ways (e.g., A/B or adaptive designs). We reiterate the importance of rapidly creating and testing iterations that can be efficiently deployed, allowing for rapid generation of data and feedback to inform future solutions (Graham et al., 2019).

Ideally, such monitoring and adjustment could be accomplished by an outcome optimization team. The team would include intervention designers, content experts, information scientists

and statisticians, technology partners, oversight members (including consumers), and resources including those necessary to implement and maintain the screen, database, and delivery software. Comparable teams exist in many consumer-oriented companies and digital mental health services.

Identifying or creating an organization with sufficient resources to maintain the optimization team and outcomes is a challenge of this model. However, outcome optimization studies are ideal for populations covered by the same insurer, where routine assessments could be built into practice. They also could occur in practice networks, through organizations (e.g., NEDA) that already offer widespread screening, or through partnerships with shared goals. Another option is establishing a researcher consortium, using a shared platform and uniform database, where different groups address complementing issues. This is a more practical approach but requires integrating information from individual studies or components into a larger picture. The model's challenges are daunting, but providing affordable, accessible, evidence-based interventions to people with EDs who are otherwise without treatment is worth the effort to determine how this could be done.

An Idea Worth Researching

We propose a model for digitally-enhanced, defined population outcome optimization with a clear goal: to achieve high rates of clinically-significant outcomes in individuals with EDs identified through online screening. A dynamic (i.e., continuously updated) database that monitors all parameters—reach, uptake, engagement, and outcome—is critical. The idea worth researching is to determine if an optimization outcome model produces significantly higher rates of clinical improvement at a population level than do current approaches, in which traditional interventions are only offered to the few people who are interested in and able to access them. Addressing provider and health care system factors also is needed to improve the treatment gap.

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