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Just-in-time adaptive interventions: A novel approach for enhancing skill utilization and acquisition in cognitive behavioral therapy for eating disorders

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Abstract

Objective: The most widely researched treatment for bulimia nervosa (BN) and binge-eating disorder (BED) is cognitive behavioral therapy (CBT), a present-focused, active, skill-oriented treatment. However, despite the success of CBT, many patients fail to achieve sufficient rates of skill utilization (i.e., the frequency with which a patient practices or uses therapeutic skills) or adequate skill acquisition (i.e., the ability to successfully perform a skill learned in treatment) by the end of treatment and outcomes suffer as a result. One method for improving skill acquisition and utilization in patients with BN or BED could be the augmentation of in-person treatment with just-in-time adaptive interventions (JITAI), which use smartphone technology to deliver real-time interventions during app-identified moments of need. The current article discusses how novel JITAI systems that utilize machine learning or other predictive algorithms could be used to detect momentary risk for eating disordered behavior and provide tailored interventions to enhance outcomes. We will consider technologies that may help reduce patient burden and suggest avenues for future research on developing acceptable and effective JITAI that can be used as an adjunct to CBT protocols.

Keywords

binge-eating disorder; bulimia nervosa; cognitive behavioral therapy; machine learning; technology

1 | OUTCOMES FROM COGNITIVE BEHAVIORAL THERAPY

Cognitive behavioral therapy (CBT) is the most researched treatment for bulimia nervosa (BN) and binge-eating disorder (BED) and typically produces large improvements in symptoms of BN and BED by the end of treatment (Fairburn et al., 2009; Hay, Bacaltchuk, Stefano, & Kashyap, 2009). CBT strives to improve BN and BED symptoms by encouraging patients to use two core treatment strategies: (a) reducing dietary restraint (e.g., eating at regular intervals throughout the day and eating a sufficient number of calories, eating a range of foods) and (b) increasing adaptive responses to eating disorder (ED) cues (e.g.,

recognizing internal and external cues for ED symptoms and adaptively regulating mood and negative affect). A strong body of literature suggests that when individuals with BN or BED are able to effectively reduce dietary restraint, CBT can produce large improvements in BN and BED symptoms. Although less well-studied, failing to respond adaptively to ED cues (particularly difficulty regulating negative affect) is associated with the maintenance of BN and BED symptoms (Leehr et al., 2015; Wilson, Fairburn, Agras, Walsh, & Kraemer, 2002). Additionally, emerging evidence suggests that improving management of negative affect during CBT predicts symptom remission (Peterson et al., 2017; Wilson et al., 2002).

Although CBT is often an effective treatment for individuals with BN or BED, only 50–60% of patients are abstinent from bingeing and purging symptoms after treatment (Fairburn et al., 2009; Hay et al., 2009; Wilson & Zandberg, 2012). Trials that have examined predictors of outcome suggest that frequent use of core CBT strategies such as regular eating (Hildebrandt et al., 2017; Zenguei, West, & Zandberg, 2014) and resisting food cues and negative affect (Wilson et al., 2002) are associated with better treatment outcomes. Successfully performing the core treatment strategies of CBT requires patients to acquire and utilize a number of skills (e.g., planning ahead and problem solving, identifying cognitions, physiological sensations, and emotions, recognizing the antecedents for binge episodes and identifying a potential coping strategy). Poor utilization of CBT strategies (and ultimately, poor treatment outcomes) may thus, in part, be due to suboptimal rates of skill acquisition (i.e., the ability to successfully perform a skill learned in treatment) and utilization (i.e., the frequency with which a patient practices or uses therapeutic skills). Developing and evaluating novel methods to improve skill acquisition and utilization in CBT is therefore a clear research priority in improving treatment outcomes for BN and BED.

2 | JUST-IN-TIME ADAPTIVE INTERVENTIONS, APPEAR WELL SUITED TO IMPROVING SKILL ACQUISITION AND UTILIZATION

The use of mobile health technologies (mHealth) to augment inperson CBT is a novel approach that could address the barriers to skill acquisition and utilization. One promising form of mHealth technology, ecological momentary interventions (EMIs), can deliver interventions to people as they go about their daily lives (originally delivered through palmtop computers, text messages, or phone calls, but more recently, through smartphones) (Heron & Smyth, 2010). This ability to intervene outside of the therapy office could increase between-session skills use by providing reminders, instructions, or motivational messages. EMI systems show promise in the treatment of numerous physical (Hamine, Gerth-Guyette, Faulx, Green, & Ginsburg, 2015) and mental health concerns (Versluis, Verkuil, Spinhoven, van der Ploeg, & Brosschot, 2016). In randomized controlled trials of mental health EMI systems, the addition of EMI was associated with a medium ($g = 0.40$) average effect size improvement on change in clinical outcomes (Versluis et al., 2016). A recent meta-analysis of the impact of mobile technology (including, but not limited to, smartphone apps that use EMI) on psychotherapy and behavioral interventions found that mobile technology boosted the impact of treatment (Pooled Effect Size = .27, $p < .05$) (Lindhiem, Bennett, Rosen, & Silk, 2015). Despite very limited data on the mechanisms through which EMIs result in

improved outcomes, improvements in skill acquisition and utilization are thought to be one of the most likely pathways (Lindhiem et al., 2015).

Although EMIs show promise, existing systems largely fail to deliver highly targeted and personalized interventions or identify the most important moments to deliver an intervention. Interventions that are personalized, contextually relevant, and received during a moment of need are more likely to facilitate the use of appropriate skills and strategies. Just-in-time adaptive interventions (JITAI) are an emerging intervention design that determines the timing and content of EMIs from real-time analysis of data (Spruijt-Metz & Nilsen, 2014). JITAI deliver interventions tailored to the person's current experiences, which may increase the acceptability and efficacy of EMIs. Sophisticated JITAI utilize machine learning or other predictive algorithms that automatically adjust in response to user and contextual data (Noordenbos, Aliakbari, & Campbell, 2014). Machine learning algorithms are widely used for predictive analytics to identify trends in data over time without preexisting knowledge and continuously improve predictive ability in response to new data. The few mHealth apps that incorporate machine learning are still nascent but have shown particular promise (Bae, Chung, Ferreira, Dey, & Suffoletto, 2017; Burke et al., 2009). For example, our team developed a JITAI developed with a machine learning algorithm to detect risk of lapsing from a weight loss diet and intervene when risk is detected. This JITAI produced superior weight losses ($n = 21$, weight loss = 4.88%) when used in conjunction with a commercial weight loss app compared to use of the commercial weight loss app alone ($n = 16$, weight loss = 2.98%). Despite these early successes, JITAI are still relatively rare and most only intervene on concrete behaviors that are easier to objectively record (e.g., physical activity). The ability of JITAI to intervene on less concrete behaviors (i.e., therapeutic skill acquisition and utilization) remains largely unknown, because JITAI have yet to be tested as a complement to a full CBT protocol.

3 | USING JITAI TO IMPROVE ACQUISITION AND UTILIZATION OF SKILLS AND STRATEGIES IN CBT FOR BN AND BED

The promise of EMIs and JITAI to augment treatment and improve outcomes is a ripe area for future study. However, the findings from the few studies of EMIs for BN are already out of date given the recent advances in technology. For example, an aftercare intervention delivered through palm-top computers resulted in high attrition (Norton, Wonderlich, Myers, Mitchell, & Crosby, 2003). Increased acceptability was found for text messages as an adjunct to CBT for BN, which resulted in small reductions in binge/purge episodes, although there remained substantial room for improvement (Shapiro et al., 2010). To date, no study has evaluated a JITAI for BN or BED despite the promise of this intervention modality.

A JITAI targeting skill acquisition and utilization in CBT for BN and BED may be feasible to develop. Disordered eating behaviors can be reliably predicted by specific internal (e.g., hunger, low mood) and external (e.g., presence of highly palatable food, time of day) cues, suggesting that optimal moments for intervention delivery can be well identified (Juarascio, Manasse, Goldstein, Forman, & Butryn, 2015). The type of data needed to inform a machine learning algorithm is already collected via CBT self-monitoring forms. Electronic self-

monitoring systems could easily collect real-time data that could refine the content and timing of the JITAI. For example, a JITAI could quickly detect and intervene when a patient eats irregularly (e.g., when the patient reports skipping a meal, when no eating episode has been recorded in over 5 hrs) or restricts eating (e.g., when the patient reports choosing only “safe” foods). A JITAI could also intervene when urges or negative affect is reported by suggesting relevant skills learned in treatment (e.g., urge management, alternative activities). JITAI used in conjunction with a clinician could offer an associated clinician portal where the specific content of the interventions could be personalized for each patient. These examples reflect only a sample of the ways in which a JITAI could work to improve skill utilization and acquisition in CBT for BN and BED.

4 | HOW TO CREATE A LOW BURDEN JITAI

Despite the theoretical promise of JITAI as an augmentation to CBT, developing an effective JITAI will likely be difficult. JITAI can be powerful tools, but the validity of machine learning algorithm predictions and the delivery of appropriate interventions are largely reliant on available data quality and quantity. Developing minimally burdensome data collection is necessary for feasible and acceptable JITAI systems to augment treatment in real-world settings. Most existing JITAI rely on active data collection, typically by requiring patients to initiate survey completion at relevant times or responding to semi-random prompts (e.g., ecological momentary assessments, EMAs) throughout the day. Whereas initial compliance with EMA is high during brief, time-limited studies, long-term compliance deteriorates over time. For example, compliance with EMA in the previously described weight loss JITAI during week 1 was high (92.14%; $SD = 7.13$) but dropped (76.08%; $SD = 2.70$) by week eight (Forman et al., in press). Our work found that while patients are excited that JITAI can increase awareness of difficult to detect cues and behavior and support skill practice in vulnerable moments, they voiced concerns about the feasibility of long-term use due to the high data entry and response burden (Godfrey, 2017). The ability to collect high quality data over long periods of time likely requires the use of user-centered design to develop minimally burdensome and intuitive data entry platforms. However, even well-designed systems are likely to carry some degree of user burden, suggesting that alternative ways to minimize active data collection are worth exploring.

Passive data collection (via phone-based or wearable sensors) may be required to adequately reduce user burden. For example, studies of JITAI for smoking and drinking cessation have previously used GPS technology to passively detect when an individual might be at a high risk location (e.g., at a bar) (Gustafson et al., 2014; Naughton et al., 2016) and similar technology could be used to identify high risk locations for binge eating (e.g., grocery stores, restaurants). Our team is currently researching whether physiological signals (e.g., heart rate variability, electro dermal activity) collected via wearable sensors can prospectively predict emotional eating and binge-eating episodes and whether continuous glucose monitoring can detect regular eating and disordered eating behaviors in nondiabetic patients with BN or BED. As wearable sensor technologies become increasingly advanced, these tools could be viable candidates for reducing user burden.

Other potential methods for reducing data entry burden include optimizing machine learning algorithms that learn which data are worth collecting and which contribute minimally to risk of ED symptoms. Patients often enter treatment with baseline differences in risk factors and access to psychological and behavioral skills and strategies. For example, one patient may already be eating regular meals prior to starting treatment whereas another may eat little outside of binge episodes. For the first patient, assessing regular eating for 20 weeks may present high data entry burden on the user while offering little benefit (as there are likely to be few intervention opportunities). Skills most relevant to individual patients may also change throughout treatment with the development of competencies in some skill domains, but continuing support needed in others. Data entry interfaces that change over time in response to individual variability identified by a machine learning algorithm could create increasingly personalized and efficient data entry systems that increase the acceptability of JITAIs.

5 | INTEGRATING JITAIS INTO TRADITIONAL PSYCHOTHERAPY

One central question in the application of JITAIs for EDs is how JITAIs could integrate with traditional psychotherapy formats. JITAIs could be designed to replace, augment, or be a gateway to traditional evidence-based interventions, all of which may hold promise for some subsets of individuals with an ED. For example, JITAIs could be designed as an app-guided self-help program and would likely be effective for some individuals (likely the same individuals who would benefit from existing CBT self-help and guided self-help resources) (Wilson & Zandberg, 2012) and serve as a method for increasing access to care. However, existing behavioral health EMIs/JITAIs studied to date appear to be less effective as standalone interventions and are most effective when used in conjunction with intervention from a mental health provider (Versluis et al., 2016), suggesting that stand alone JITAI systems are unlikely to work well for most patients. Alternatively, consistent with a stepped care model (Wilson, Vitousek, & Loeb, 2000), JITAIs could be used as a preliminary entry point to treatment with individuals who fail to benefit from a standalone JITAI getting triaged into more intensive, face-to-face therapy. Although a stepped care model has a number of benefits, there are also risks involved in failing to intervene effectively early in treatment and potentially difficulties with connecting patients using a standalone JITAI to appropriate treatment resources. Thus, although JITAIs may hold promise as a stand-alone intervention platform for some individuals, identifying how best to use JITAIs as an augmentation to traditional psychotherapy or as a way to extend the gains made during treatment and prevent relapse is likely an optimal area for a future research agenda.

When implementing JITAIs in conjunction with face-to-face psychotherapy, a number of questions emerge about how to best integrate and support an existing treatment. For example, should a JITAI be used for the full treatment duration or would it be more effective to use a JITAI during certain key periods of treatment? Given the growing evidence suggesting the importance of early response to treatment (Grilo, Masheb, & Wilson, 2006; Linardon, de la Piedad Garcia, & Brennan, 2017), the first 4 weeks of CBT may be an optimal time period to implement a JITAI that supports early skill development and treatment adherence. Conversely, toward the end of treatment, as the patient begins to attend therapy sessions less often or enters the maintenance period, a JITAI could serve as a bridge

between sessions. To date, the vast majority of JITAI systems deliver short-term interventions. It remains unknown how long patients will be willing to use and respond to JITAI before engagement drops off or benefits are no longer seen. Similarly, questions emerge about the optimal duration and frequency for a JITAI designed to augment an existing treatment. For example, Should frequency of interventions be modified throughout treatment? A higher frequency of interventions early in treatment may be helpful as patients learn and acquire a number of new skills, but some patients may be overwhelmed by numerous daily interventions in the beginning of treatment and may benefit more from less frequent interventions, even if the algorithm detects a need for skill use. Future research needs to focus on determining the optimal length and frequency of JITAI to minimize patient burden and maximize therapeutic benefit through optimal skill acquisition and utilization.

Other considerations for integrating JITAI into traditional psychotherapy include questions regarding the degree of training and support needed for therapists to be able to efficiently learn a new system and seamlessly incorporate information gathered from JITAI into their practice. JITAI systems can replace existing self-monitoring forms and provide valuable data to clinicians regarding triggers for disordered eating behavior and the patient's use of skills and strategies between sessions. However, the time needed to review this information ahead of session in a clinician portal or time needed to review it with the patient during a session could become a barrier to use unless the system is designed to provide key information to the therapist with little additional burden. For example, in a recently developed JITAI by members of our team, we found that a feature of the clinician portal that allowed clinicians to graph potential triggers against disordered eating behaviors was rarely used by clinicians because it was perceived as providing too much information about all possible triggers rather than identifying the most notable triggers for their patient. Although clinicians for this project reported ahead of time that they expected this feature to be particularly helpful, the amount of time needed to adequately use the feature made it prohibitive to incorporate into treatment. Similarly, while we anticipate that any JITAI offered to clinicians unfamiliar with the technology (i.e., not the researchers who built it) would include training materials to guide clinicians through the steps needed to use this tool with patients as a lengthy training process itself could be a barrier to use for a busy clinician. Apps are already being increasingly used to support numerous aspects of therapy (e.g., self-monitoring, relaxation exercises, cognitive restructuring, psychoeducation) and given the sheer number of available apps, it is difficult for clinicians to develop knowledge of and expertise in all available apps that a patient may wish to use during treatment. It is our experience that patients often request use of apps that are unfamiliar to the clinician. In these cases, we support a collaborative approach to using the technology as a tool for therapy where both clinician and patient work together to understand how the app and its tools can best support therapy goals. However, as JITAI systems become increasingly more sophisticated, it is essential that a user-centered design approach is used to ensure that both patients and clinicians can easily and quickly understand how to appropriately use the JITAI system to augment treatment.

6 | CONCLUSION

Although there remains a number of unanswered questions and substantial need for additional research, the increasing sophistication and widespread use of mobile technologies offers many promising avenues for the use of innovative technological augmentations to improve outcomes from CBT. Although we largely discussed applications of JITAIs as an augmentation to CBT, similar JITAI systems could likely support a number of skill-based psychotherapies for EDs (e.g., dialectical behavior therapy, family-based treatments). We believe JITAIs provide enormous potential to enhance our conceptual understanding of psychotherapeutic processes as they can collect information from patients in their daily lives, without relying heavily on retrospective recall or insight, and test out which skills might be most effective given the patients' unique context. The use of novel JITAIs to augment treatment for BN and BED is clearly an area worth researching.

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