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Evidence-Based Strategies for Treatment Personalization: A Review

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Clinicians in practice routinely make decisions that, in effect, tailor the care they provide to each individual patient. For example, clinicians must decide which treatment package to administer, or what specific skills to introduce. Providers also determine when to change approaches, the frequency of sessions, and when to terminate treatment. In this review, we describe the empirical literature for personalizing the delivery of psychological care that corresponds to the inflection points in treatment that clinicians face. In addition, we provide data-based recommendations to clinicians for personalizing patient care at each of these decision points and suggest areas for future study.

Over the past 50 years, the field of clinical psychology has witnessed an influx of intervention development, along with related efficacy testing, for a range of mental health difficulties. These advances in treatment research are likely due to several important shifts in the landscape of clinical psychological science. First, methods of scientific verification were enhanced during the 1970s and 1980s, resulting in an ability to more rigorously demonstrate the efficacy of psychological interventions (e.g., Barlow et al., 2009). Another important shift in the field was prompted by the publication of the third edition of the *Diagnostic and Statistical Manual of Mental Disorders* (*DSM-III*; American Psychiatric Association [APA], 1980). This revolutionary approach to diagnosis replaced broad conceptions of psychopathology (e.g., neuroses) with standardized sets of symptoms, allowing treatment developers and researchers to determine whether their interventions were associated with change in discrete and consistently defined clinical presentations (i.e., *DSM* disorders). Finally, the pioneering work of Strupp (1973) highlighted the need to sufficiently define the therapeutic procedures of new treatments so that others could deliver them as intended.

As a result of these advances, detailed therapeutic protocols tailored to specific *DSM* diagnoses have amassed considerable empirical support (see: Carpenter et al., 2018; Cristea et al., 2019; Cuijpers, Karyotaki, et al., 2014). In fact, positive outcomes treating discrete disorders with manualized interventions, accompanied by a growing mandate for evidence-based practice by heath care policy-makers and third-party payers (Baker, 2001; Barlow, 1996, 2004), has led to numerous evidence-based forms of psychotherapy (e.g., cognitive-behavioral therapy [CBT], interpersonal therapy [IPT]), manualized intervention protocols (e.g., Mastery of Your Anxiety and Panic [Barlow & Craske, 2007], Dialectical Behavior Therapy [Linehan, 1993]), and specific therapeutic skills (e.g., cognitive reappraisal, exposure, mindfulness training).

Given the plurality of interventions with demonstrated efficacy for each *DSM* diagnosis, practicing clinicians must make a number of decisions to tailor the psychotherapy they offer to individual patients. For instance, clinicians often select a therapeutic approach or manual for a given patient from available alternatives. Or, if a more eclectic approach is taken, therapists choose which therapeutic elements (e.g., mindfulness, assertiveness training) to include in a course of care. Treatment providers also make decisions about when to change approaches in therapy (e.g., shifting from one skill to another based on non-response), how frequently to meet (e.g., weekly, every other week), and when to terminate treatment. In this review, we will characterize the various decision points that clinicians face when providing psychotherapy and summarize the research that has been conducted to establish evidence-based rules for guiding these therapeutic choices. Given that much of this research is in

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its early stages, we also denote future research questions that should be addressed to help frontline clinicians make the most empirically sound decisions for their patients. Overall, our goal is to arm clinician with up-to-date treatment personalization research to the choices they make when providing services.

Personalizing Therapy Based on the Treatment Package Administered

Empirically supported treatments are protocols that have been tested in efficacy trials and have amassed sufficient support for their use within particular patient populations (Kazdin, 2011). Although the development of interventions that successfully address a variety of mental health conditions is important for easing the burden of disease, the growing number of efficacious protocols may make it difficult for clinicians to choose the best approach for a specific client from available alternatives. For example, the Society of Clinical Psychology, also known as Division 12 of the American Psychological Association (APA), provides a list of treatments for each mental health diagnosis that has demonstrated the "best research evidence" according to guidelines set forth by the APA Presidential Task Force on Evidence-Based Practice (2006). In this list, 14 discrete treatment packages are included for major depressive disorder (MDD) alone, with little guidance on how to select the best approach for an individual patient (APA, 2015).

Perhaps contributing to the difficulty of predicting an advantage for one treatment package relative to another for a given patient, studies describing nomothetic comparisons of more than one active intervention have generally found equivalent effects. For example, a meta-analysis that compared the effects of 134 active treatments for depression (e.g., CBT, IPT, Problem-Solving Therapy, Behavioral Activation, antidepressant medication) found similar improvements across conditions (Cuijpers, Sijbrandij, et al., 2014). Treatment outcomes were assessed by response rate (50% score decrease on a depressive measure), remission rate (score at or below a 7 on the Hamilton Depression Rating Scale), and whether or not a patient met criteria for MDD (established by a standardized diagnostic interview). Symptom improvement was equal across all types of psychotherapy, regardless of outcome measurement.

Despite limited evidence of nomothetic differences in efficiency between treatments, certain patient characteristics may predict whether a given individual is more likely to respond to one treatment relative to others. For example, factors such as being married, employed, or having experienced recent life stressors have been shown to predict better response rates for CT/CBT compared to antidepressant medication (ADM) in moderate to severely depressed outpatients (DeRubeis et al., 2014; Fournier et al., 2009). In contrast, presence of a comorbid personality disorder has been associated with more favorable outcomes for ADM relative to CT/CBT (DeRubeis et al., 2014; Fournier et al., 2008). When evaluating treatment response in trials comparing CT/CBT to IPT, patients with cognitive problems improved more with IPT, whereas individuals with somatic complaints, paranoid symptoms, interpersonal self-sacrificing, and co-occurring personality disorders exhibited more favorable outcomes with CT (Huibers et al., 2015; Joyce et al., 2007).

Using these moderators, researchers have developed models that match patients to their ideal treatment package. For example, Barber and Muenz (1996) used data from the Treatment of Depression Collaborative Research Program (Elkin et al., 1989) to compute a "matching factor" that predicted whether CT or IPT would be most effective for an individual based on pretreatment marital status, levels of avoidance and obsessiveness, and depression symptom severity. An individual's matching factor is a composite score combining patient-specific factors and treatment main effects; in this trial, positive matching factor values suggest that a patient would be more responsive to CT, whereas negative scores favor IPT. Utilizing data from the same trial used to develop the matching factor, the authors retrospectively determined that patients assigned to their matched treatment showed significantly larger decreases in depressive symptoms, relative to those assigned to the alternative (i.e., nonoptimal) treatment (Barber & Muenz, 1996).

A closely related method that builds on Barber and Muenz's (1996) approach to determine the optimal treatment for individual patients is DeRubeis and colleagues' treatment selection algorithm, the Personalized Advantage Index (PAI; DeRubeis et al., 2014). An individual's PAI indicates the degree to which they would benefit from receiving their optimal versus nonoptimal treatment. For some patients, this difference may be minimal, suggesting they would benefit equally from alternative treatments, whereas for others the difference in treatment outcomes may be quite large. Generally, in trials for which the PAI has been retrospectively applied, patients that were randomly assigned to their predicted optimal treatment fared better than those assigned to their predicted nonoptimal treatment. In its first trial, the PAI showed a clinically meaningful advantage of one treatment over the other (i.e., ADM compared to CBT) in 60% of the sample (DeRubeis et al., 2014). Further, when the PAI was recently applied in a study comparing CT to IPT for depression, post-hoc analyses demonstrated that patients randomized to their optimal treatment showed significantly greater improvement compared to patients receiving their nonoptimal treatment (Huibers et al., 2014). Similarly, Deisenhofer et al. (2018) used the PAI to predict treatment outcome in a naturalistic sample of patients with PTSD receiving either trauma-focused CBT (TF-CBT) or eye movement desensitization and reprocessing (EMDR). In that analysis, 63% of patients who received their optimal treatment showed reliable improvement whereas only 33.7% of patients who received their suboptimal treatment demonstrated such effects (Deisenhofer et al., 2018).

In contrast to the statistical strategies described above (i.e., PAI, matching factor), prescriptive psychotherapy (PT) provides guidance to clinicians for selecting treatment approaches based on the patient's level of impairment, coping style, level of distress, and levels of interpersonal resistance to external influence (Beutler & Harwood, 2000). Specifically, Beutler and colleagues (2000) offer 10 guiding principles (e.g., "benefit corresponds with treatment intensity among functionally impaired patients," "therapeutic change is most likely if the initial focus of change efforts is to build new skills and alter disruptive symptoms") for selecting treatment methods; this method relies on baseline assessments to advise treatment personalization at the outset. Although PT has been shown to evidence clinically significant change, comparing PT to cognitive therapy and narrative therapy resulted in no differences in treatment outcome as a function of treatment type (Beutler et al., 2003).

The personalization methods described so far consider the differences in symptom presentation and characteristics of each patient, but fail to include patient preferences in treatment planning. The shared decision making (SDM) model has been used to address this issue by facilitating collaboration between patients and their clinicians when determining the course of treatment. SDM assess how well a given evidence-based treatment aligns with the patient's needs through the reciprocal exchange of information, identification of patient values and preferences, discussion of treatment options, and agreement on a treatment plan (Langer & Jensen-Doss, 2018). Across studies of treatment for depressed adults, SDM was associated with similar treatment outcomes but greater patient satisfaction (Loh et al., 2007; Swanson et al., 2007). Furthermore, patients in an SDM group showed greater improvements in psychiatric and drug use problems, measured by the EuropASI, at 3-month follow-up compared to those receiving standard procedure for planning treatment in substance abuse treatment centers (Joosten et al., 2009). However, these findings were not replicated on the measures of primary substance use and dependence. These results suggest that SDM may increase patient satisfaction with treatment, although it is still unclear if including patients in personalized treatment selection decisions also led to improved treatment outcomes.

Including client preferences in psychotherapy decision making also facilitates collaboration among therapists and clients by assessing the specific conditions and activities that a client wants in their treatment. Specifically, taking into account activity (e.g., homework), treatment (e.g., specific protocols), and therapist (e.g., demographic match) preferences may decrease early dropout and improve treatment outcomes. Indeed, a meta-analysis of 53 studies assessing client preferences found that clients who were not matched to their preferences or not given a choice of treatment were 1.79 times more likely to terminate treatment prematurely and evidenced worse treatment outcomes compared to those who were matched to their preferences (Swift et al., 2018).

Together, this line of research suggests it is important that patients be matched to the appropriate treatment to achieve optimal outcomes. Certain predictive variables may moderate treatment outcomes and could be used to inform treatment decisions. Although the models described above advance our understanding of the best way to personalize treatment, randomized controlled trials are needed to determine if (a) these predictive variables generalize to influence outcomes in different samples and (b) these findings can be replicated in prospective studies. Additionally, more research is needed to validate the PAI approach as replication has proven problematic. Not only are large sample sizes required to see reliable effects when using this approach (Luedtke et al., 2019), some have argued that the effects reported in the precision treatment literature are smaller than what is typically considered (Lorenzo-Luaces et al., 2021). Although SDM fosters patient satisfaction with treatment, there are mixed findings with regard to whether this approach improves treatment outcomes. Future research should analyze the feasibility of implementing these strategies, whether Swift et al. (2018) inclusion of client preferences outperforms SDM, and generalizability of these finding to clarify how to effectively implement treatment selection in clinical practice. Clinicians should take into consideration these moderating variables when choosing the appropriate treatment for a given client and collaborate with the client to determine course of care (Figure 1).

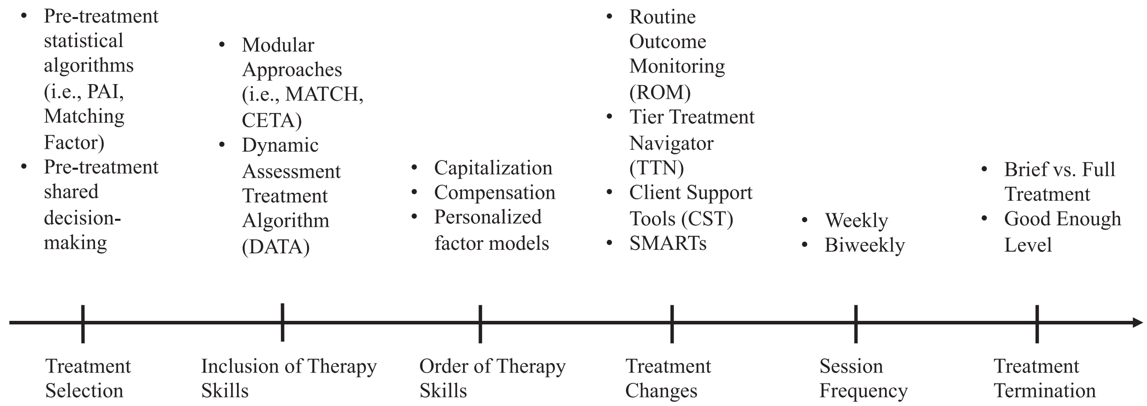

Figure 1. Conceptual Mapping of personalization Approaches.

Personalized Inclusion of Therapeutic Elements (Skills)

In community practice, clinicians may apply an eclectic approach to treatment in which a collection of therapeutic skills (e.g., mindfulness training, behavioral activation) are selected for a given patient, rather than adhering to a prescribed manual (Chorpita et al., 2005a). Unfortunately, there are few data-driven methods to help clinicians choose the most appropriate elements for each patient. Chorpita et al. (2005b) attempted to address this limitation by categorizing components derived from existing evidence-based treatments for anxiety, depression, traumatic stress, and behavioral problems in youth into 33 distinct modules. The Modular Approach to Therapy for Children (MATCH; Chorpita & Weisz, 2005) provides a menu of treatment strategies with a decision flowchart that suggests modules to use with each patient based on their primary diagnosis.

Instead of typical evidence-based care in which patients sequentially complete full treatment protocols corresponding to each assigned diagnosis, MATCH is designed to reduce redundancies by distilling the common components across interventions. Although MATCH provides a default module sequence determined by patient diagnoses, clinicians have the flexibility to modify this order and to add supplemental modules. With regard to outcomes, Weisz et al. (2012) found that children treated with the MATCH protocol demonstrated significantly faster improvements compared to children assigned to complete standard evidence-based protocols. These results suggest that a personalized approach to therapy may be more efficient than standard care, although more research is needed to specify the optimal method to select and order modules.

Similar to the MATCH approach, modular interventions have also been applied to adults in low- and middle-income countries. Specifically, in the Common Elements Treatment Approach (CETA), initial module selection is based on symptom presentation, though therapists can add modules according to patients' specific needs (Murray et al., 2014). Much like MATCH, CETA includes a default sequence for each disorder that providers can modify as issues arise in treatment or if symptoms are still present after the initial sequence is complete. CETA has been implemented in two randomized controlled trials in Iraq and Thailand to treat patients experiencing posttraumatic stress symptoms (Bolton et al., 2014; Weiss et al., 2015). In both trials, CETA was effective in reducing symptoms of depression, anxiety, and posttraumatic stress compared to waitlist control conditions. Further, CETA demonstrated greater global reductions in mental health problems compared to CPT (Weiss et al., 2015).

In another attempt to personalize the selection of treatment components, Fisher and colleagues (Fisher & Boswell, 2016; Fisher et al., 2019) used the modules of the Unified Protocol (UP; Barlow et al., 2011), a transdiagnostic cognitive-behavioral intervention, as a treatment "menu." Based on clinician judgment, they matched each UP module to a specific symptom domain. For example, the understanding emotions module and the mindful emotion awareness module were provided to patients with high levels of pretreatment negative affect, whereas the cognitive flexibility module was used to target worry and feelings of worthlessness. To determine which modules to assign to each patient (and in what order), patients were asked to complete questionnaires measuring *DSM-5* symptoms of generalized anxiety disorder and major depressive disorder, in addition to behavioral symptoms such as avoiding activities, procrastinating, and reassurance seeking, four times per day for 30 days before starting treatment. Next, a person-specific factor analysis was used to identify predominant pathological dimensions, which, in turn, guided module selection; the researchers argue that only the modules related to individual pathology should be administered, allowing clinicians to leave out the irrelevant skills.

Results from the person-specific analyses were interpreted either by the researchers or a computerized algorithm (i.e., dynamic assessment treatment algorithm [DATA]; Fernandez et al., 2017). Regardless of the method of interpretation, participants demonstrated significant reductions in depressive and anxiety symptoms in response to their personalized UP treatment. Although these results suggest the personalization of treatment modules influences outcomes, the study lacked a standard treatment condition, making it difficult to determine if a dynamic assessment and modeling approach to personalization is more efficient or efficacious than treatment as usual. Additionally, it is worth noting that, among the case examples used to illustrate this approach, patients received the majority of the UP modules in a similar order as the standard UP presentation, raising questions about the degree to which module selection was actually personalized.

Rather than relying on relatively transient symptoms to personalize treatment, some researchers have argued that individual differences in personality may be more powerful or generalizable predictor variables (e.g., Mullins-Sweat et al., 2020). Dimensional personality ratings may provide more specificity for personalizing care than treatment manuals designed for individual DSM disorders (e.g., providing dialectical behavior therapy [DBT; Linehan, 1993] for all patients with borderline personality disorder [BPD]). For example, according to *DSM-5* (American Psychiatric Association, 2013), there are 256 possible symptom combinations a person could endorse to meet criteria for BPD and two people could meet criteria for the same diagnosis of BPD by only endorsing one symptom in common. Because this condition's symptom presentation is quite heterogeneous, it is unlikely that the same therapy will successfully treat each variation. In contrast, characterizing psychopathology with dimensional models of personality (e.g., the Alternative Model of Personality Disorders for DSM-5 [AMPD]; American Psychiatric Association, 2013) allows clinicians to rate patients on a limited number of traits (e.g., negative affectivity, detachment, antagonism, disinhibition, and psychoticism) and select treatment elements/modalities accordingly. For example, some have hypothesized that individuals with high levels of conscientiousness would benefit more from cognitive-behavioral approaches due to its organization and use of homework elements (Widiger & Presnall, 2013).

Moreover, specific treatment components have been suggested to correspond with high and low extremes of each domain (e.g., negative affectivity, antagonism) of popular personality models. For example, the UP is associated with significant decreases in negative affectivity, relative to single-disorder CBT, in patients with principal anxiety disorders (Sauer-Zavala, Fournier, et al., 2020). Similarly, Craske et al. (2019) have developed an intervention to specifically address positive affect. Additionally, CBT and IPT have been described as likely to increase prosocial behavior, thus reducing antagonism, whereas CT has been suggested to reduce psychoticism by providing reality checks (Bach & Presnall-Shvorin, 2020). To our knowledge, no studies have tested whether personality-based treatment selection results in stronger or more efficient symptom reduction than standard care selected based on DSM diagnosis. This may be a promising avenue for future research (Mullins-Sweat et al., 2020).

A personalized approach to selecting treatment elements may reduce the amount of sessions required for clients to evidence clinically significant improvements. Additionally, by selecting elements that target an individual client's unique needs may increase motivation and treatment satisfaction. Adopting a modular approach to treatment may be more advantageous for personalized care than a single-disorder approach.

Personalized Order of Therapeutic Elements

In addition to personalizing the *selection* of treatment elements that are delivered to a particular patient, the *order* in which those elements are presented may also be tailored based on individual characteristics. For example, in Fisher and colleagues' (Fisher & Boswell, 2016; Fisher et al., 2019) data-driven approach to sequencing, a dynamic factor model was used to determine the temporal relationships among symptom dimensions in order to inform module ordering such that elements targeting symptoms that appeared to drive other problems were administered first. Because this program of research explored both module selection and sequencing in the same studies, it is difficult to draw conclusions about the importance of the modules that were selected versus the order in which they were presented.

Whereas Fisher et al. have used relations among symptoms to personalize treatments, other researchers have used patients' therapy skills at baseline. Cheavens et al. (2012) utilized a capitalization versus compensation framework where capitalization refers to the prioritization of patients' relative strengths, whereas compensation focuses on relative deficits. Of note, these skills are deemed strengths or deficits relative to each patient's other skills and not to nomothetic skill levels so that every patient exhibits personal strengths and deficits. In this RCT, the researchers selected two modules (from a bank of four possibilities) that were relative strengths or relative deficits to implement with 34 adults with MDD (Cheavens et al., 2012). Relative strengths and deficits were determined by a semistructured interview wherein evaluators determined each patient's frequency of use and mastery of cognitive strategies, interpersonal skills, behavioral activation, and acceptance practices. Following the interview, all evaluators and supervisors met to reach a consensus for each patient's two greatest strengths and two greatest deficits. Patients randomized to the capitalization condition received the modules focused on building skills for which they already demonstrated competence, whereas those randomized to the compensation condition focused on their skill deficits. The results of this study suggest that capitalizing on existing strengths was associated with faster symptom improvement that was maintained over the course of treatment compared to compensating for weaknesses.

In another study testing the feasibility of ordering modules according to patient strengths and deficits, Sauer-Zavala et al. (2019) conducted a single-case experiment ($N = 12$ completers) in which modules of the UP were sequenced based on pretreatment strengths and deficits in adults with anxiety and depressive disorders. To determine strengths and deficits, patients completed evidence-based questionnaires designated to measure the skills targeted by each module. For example, the Beliefs About Emotions Scale (BES; Rimes & Chalder, 2010) was used to assess competence with the Understanding Emotions module and the Southampton Mindfulness Questionnaire (Chadwick et al, 2008) was used to assess skill level associated with the Mindful Emotion Awareness module. Researchers converted the total scores for each measure to standard scores, then rank ordered the modules from greatest deficit to strongest strength. Patients were randomly assigned to receive modules in sequences that prioritized their relative strengths or weaknesses. Similar to Cheavens et al. (2012), results suggest that patients in the strengths condition demonstrated a faster rate of change compared to the weakness condition (Sauer-Zavala et al., 2019).

Taken together, these finding suggest that personalizing the order of skills may reduce the number of sessions needed before clients see improvements in their symptoms, thus making treatment more efficient and cost-efficient. This emerging evidence further suggests it may be more beneficial to focus on patient strengths at the outset of treatment rather than compensating for skill deficits. Although one study in support of the compensation framework found that adults with depression who are unable to effectively pursue promotion goals evidenced greater improvement with self-system therapy (SST) compared to CT (Strauman et al., 2006), this study found no differences in overall efficacy between the two treatments. Moreover, there are many ways to measure patient skills. The studies previously mentioned utilized semistructured interviews and clinician judgment, as well as more data-driven approaches matching validated self-report questionnaires or an intensive measure of daily symptoms to skill modules. Behavioral measures of skill use may be yet another way to capture competencies that could be used to sequence care. The optimal method for measuring skill strengths is currently unclear and researcher decisions may exert an undue influence on which symptoms are deemed important (Bastiaansen et al., 2020). Clinicians should consider personalizing the order of skills to make treatment more efficient and cost-effective, thus allowing clients to progress faster and allowing clinicians to see more patients in a given time frame.

Personalized Approaches to Treatment Changes

Another challenge therapists face is knowing when to switch treatment approaches. In other words, when a patient demonstrates difficulty grasping a concept or implementing a skill, is it best to move on to another treatment component or continue to try to work through these difficulties? Relatedly, identifying likely nonresponders early on is imperative for therapists to adjust treatment before a client deteriorates further. Researchers have utilized routine outcome monitoring (ROM) to distinguish patients who are "off-track" or whose progress is stalling. Providing feedback to therapists via ROM has been shown to improve patient outcomes (Boswell et al., 2015). For example, a recent meta-analysis found that treatment with routine monitoring and feedback outperformed treatment as usual (Lambert et al., 2018). However, to be included in the meta-analysis, studies were not required to use random assignment to determine if patients received treatment with ROM or treatment as usual. Moreover, Lutz et al. (2019) developed the Trier Treatment Navigator (TTN) that predicts optimal treatment strategies for individual patients, uses ROM to identify when patients are "off-track" or at risk for treatment dropout, and provides adaptive treatment recommendations through the Clinical Problem Solving Tools (CPST). Researchers used the "nearest-neighbors" strategy to determine if a specific patient would benefit most from a motivation or problem-solving focus within the first 10 sessions. CPST provides feedback about therapeutic alliance, a client's motivation for change, suicide risk and emotion regulation as soon as a patient is identified as "off-track." CPST also suggested intervention techniques for clinicians to solve the problem. Routine monitoring of these problem areas occurred every fifth session. Patients treated with their optimal strategies (problem-solving or motivation focus) showed faster improvements compared to those treated with their nonoptimal strategy. Suicide risk and recent life events were the greatest predictors of patients becoming "off-track" throughout treatment.

Similarly, Harmon et al. (2007) compared patient outcomes when therapists received one of two types of therapist feedback based on ROM or no feedback (treatment-as-usual; TAU). Patients in both feedback conditions were new patients at a university-run clinic while the TAU data came from previous studies conducted in the clinic. All patients were asked to complete the Outcome Questionnaire (OQ-45; Lambert et al., 2004) prior to each session to provide information about subjective discomfort, relationship functioning, and social role functioning. In the therapist feedback conditions, responses to the OQ-45 at each session were used to plot an expected recovery curve to identify "off track" patients who were not meeting expected progress throughout treatment. Once a client was classified as "off track" or as a nonresponder, they were randomly assigned to receive feedback with or without Client Support Tools (CST). Patients in the CST condition completed additional questionnaires that provided the therapist with information regarding the patient's perception of therapeutic alliance, motivation for change, and level of social support. The CST condition also provided therapists with a decision tree to guide their response to these patients that first targeted difficulties with the working alliance before addressing motivation and social support issues. Among those who demonstrated early signs of nonresponse, patients in the feedback plus CST condition were half as likely to show deterioration and twice as likely to show clinically significant improvements relative to TAU. Though these studies illustrate the importance of ROM and quality of feedback, it is unclear what remedial measures were taken once a patient was identified as a nonresponder or likely to deteriorate. Empirical evidence that can inform clinical decisions to focus more in depth on certain skills or introduce a new approach is needed.

Novel research methods, including Sequential Multiple Assessment Randomized Trials (SMARTs; Almirall & Chronis-Tuscano, 2016), are being implemented to begin to inform such decision-making. For example, two trials have been conducted using samples meeting criteria for ADHD and implemented combined medication and behavioral treatment (Chronis-Tuscano et al., 2016; Pelham et al., 2016). Results from these trails highlight the feasibility and acceptableness of SMARTs and the benefits of adding low-dose medication to treatment in nonresponders. Similarly, Gunlicks-Stoessel et al. (2016) piloted a SMART with a sample of 32 adolescents with MDD, Dysthymic Disorder, or Depression Not Otherwise Specified (NOS) treated with 12–16 weeks of IPT, with or without ADM. Patients were randomly assigned to an early or late decision point (4 or 8 weeks respectively) in which their symptoms would be assessed for treatment response (less than a 20% decrease in depression scores at 4 weeks or less than a 40% decrease at 8 weeks). If identified as a nonresponder, the patient would be randomly assigned to receive four additional therapy sessions twice weekly or begin antidepressant medication; responders continued IPT for the complete 12 sessions. Patient, parent, and therapist feedback suggest that an early (4 week) decision point is optimal for treatment adjustments. Results from the full SMART may highlight the benefit of increasing session frequency in nonresponders. However, results from the pilot do not discuss the benefits of one treatment change over the other.

Practicing clinicians could benefit from implementing ROM to effectively track patient progress by more quickly identifying patients that are digressing or whose progress is stagnant. If a patient is not responding or worsening, clinicians should determine potential reasons for the lack of progress. For example, if a patient is lacking motivation to be involved in their treatment, a motivation-focused session might resolve the issue. Implementing ROM might provide better insight into why a given patient is not responding or worsening, therefore guiding clinician decision making and changes to the course of care.

Personalized Approaches to Session Frequency

Another potential strategy for treatment personalization may be related to the frequency with which sessions are delivered. Some research has suggested that more sessions per week is related to better treatment outcomes, whereas total number of sessions during treatment is not, when treating depression (e.g., Cuijpers et al., 2013). However, patients in this study were not randomly assigned to receive varying session frequencies. Bruijniks et al. (2020) compared once versus twice weekly CBT and IPT in patients with depression found that those in the twice weekly condition showed greater symptom reduction and faster improvements compared to the once weekly group. Additionally, more dropouts were observed in the once weekly group. Similarly, twice weekly treatment was compared to intensive treatment using exposure and response prevention (ERP) in adults who met DSM-IV (American Psychiatric Association, 1994) criteria for OCD (Abramowitz et al, 2003). Participants in the intensive treatment condition received sessions every weekday for 3 weeks whereas the twice weekly group received treatment for 8 weeks; in both conditions, a total of 15 sessions were provided. Patients in the intensive treatment group showed a faster rate of change but no group differences were found at follow-up. Finally, data from a university clinic suggest that patients who received weekly sessions (versus every other week) showed clinically significant improvements earlier in treatment, though both groups showed equal levels of recovery at follow-up (Erekson et al., 2015).

Taken together, these studies suggest that session frequency may be a prognostic variable in that more frequent sessions tend to lead to faster symptom improvement for most patients. However, it is unclear from these studies if there are certain factors that affect how likely an individual patient is to benefit from more frequent sessions. Indeed, attending therapy multiple days per week may be too burdensome to patients, may not align with a therapist's schedule, and may create a bottleneck effect for an organization by limiting treatment access for people more broadly. Having sessions multiple times per week should only be undertaken if there is evidence that a particular person will benefit from this frequency. Based on these findings, clinicians and patients should discuss whether more frequent sessions would be possible/preferable.

Personalized Approaches to Treatment Termination

In an attempt to make treatment more efficient and cost-effective, researchers have examined dose-response models of psychotherapy to characterize how many sessions are required to see clinically significant improvements. This work suggests that 13–18 sessions are necessary for 50% of patients to achieve clinically significant change (Hansen et al., 2002), 10% of patients demonstrate improvement after only 4 sessions, and 75% of patients show little to no more improvement after 26 sessions (Robinson et al., 2020). This pattern of results demonstrates the substantial variability between patients in the number of sessions needed for symptom change. To explore whether some individuals may benefit from fewer sessions, several research groups have tested the efficacy of abbreviated interventions. For example, Murray et al. (2018) are currently piloting a brief version of CETA (Murray et al., 2014), compared to the standard-length protocol and a waitlist condition in Ukrainian adults with depression, anxiety, PTSD or substance abuse. The brief treatment package "front-loads" elements purported to address core mechanisms of change associated with a given diagnosis. For example, a patient presenting with depression would be treated with elements of cognitive restructuring and behavioral activation. Though traditional CETA allows therapists the freedom to determine the order of treatment elements, all patients in this study receive their initial sessions in a predetermined order corresponding to the brief treatment for their primary problem. After the fourth session, patients are randomly assigned to terminate treatment at the next session (brief condition) or continue with at least three additional sessions (full condition). The elements of the additional sessions in the full condition are based on therapist discretion and the timing of treatment termination is determined by symptom presentation, client report and therapist supervision. In other words, treatment could be terminated once the patient shows significant symptom improvement, reports improvement in functioning, and the therapist's supervisor approves termination. Although results from this trial are not yet available, findings may inform clinical decision-making on when to terminate treatment and for whom it would be beneficial to continue with additional sessions. Further, more studies assessing treatment termination are necessary to ensure researchers are tracking accurate, reliable markers of early symptom change.

Using a similar study design, Sauer-Zavala et al. (2021) tested a personalized approach to treatment termination with the UP (Barlow et al., 2011) in adults with anxiety and depressive disorders. Patients were randomly assigned to receive UP treatment modules in the standard order or in sequences that prioritized their pre-treatment strengths or deficits. Strengths and deficits were determined by evidence-based questionnaires measuring the skills addressed in each module (e.g. the Southampton Mindfulness Questionnaire to evaluate skill competence related to the Mindful Emotion Awareness module). Modules were rank ordered from greatest deficit to strongest strength in the weakness condition or vice versa for strengths. Next, patients were randomly assigned to terminate treatment following their 6th session or continue for the full 12 sessions. Preliminary results from this trial suggest that patients who demonstrated reliable change on a measure of experiential avoidance (the hypothesized mechanism of the UP) and were assigned to discontinue at Session 6 show comparable outcomes at posttreatment to individuals who receive the full dose (Southward & Sauer-Zavala, 2020). This study design allows for the identification of patient-level factors that can be used to personalize treatment termination decisions. Future research should identify more treatment moderators such as employment, marital status, and comorbid personality disorders that may influence the number of sessions necessary for clinically significant improvement.

Another way of interpreting dose-response relationships in psychotherapy is the good-enough level (GEL) model that posits that patients who come for varying numbers of sessions show changes at varying rates (Baldwin et al., 2009). The GEL model suggests that because patients are staying in treatment until they and their therapist decide they have improved to a "good-enough level," the dose of treatment reflects treatment response and malleability of symptoms. This model also suggests that the number of sessions is unrelated to the likelihood of a client showing clinically significant change. Indeed, one study assessing the GEL model found that treatment dose had a nonlinear relationship with the likelihood of clinically significant change and patients' rate of change varied as a function of treatment dose (Baldwin et al., 2009). This suggests that treatment response may moderate the relationship between treatment dose and clinically significant change. However, this study utilized archival data to draw conclusions. More research is needed to understand if clinicians could prospectively determine which clients would evidence stronger treatment response and thus require fewer sessions to evidence clinically significant improvements.

Concluding Remarks

The purpose of this review was to characterize various ways to personalize the delivery of available, efficacious treatments for mental health difficulties. First, clinicians must select an intervention package from available alternatives. Although this decision is often influenced by the patient's diagnostic status (i.e., selecting a treatment for panic disorder if the patient has panic disorder as a primary disorder), emerging research suggests that certain individual characteristics (e.g., marital status, employment) may predict better outcomes in one treatment rather than another. Data-driven solutions for taking these variables into account have been identified, although additional prospective applications of these techniques are still needed. Next, within each course of care, clinicians have the flexibility to choose which therapeutic skills to administer with a particular patient. Preliminary data suggest that personalizing the skills included in an individual's treatment, along with the order in which those skills are presented, may affect treatment outcome. However, there are multiple ways to approach module selection and sequencing, and future research is needed to better understand which method yields the best results.

After treatment has commenced, clinicians are faced with additional decision points. For example, if patients do not demonstrate early improvements following the introduction of the initial intervention, clinicians must determine whether and when to switch to a second-line approach. Although routine outcome monitoring is an effective method for tracking patient progress, the suggestions for how to alter care have not been empirically validated. It is necessary for future research to identify ways to leverage the data gleaned from ongoing patient assessment to make empirically supported decisions about treatment modification. Another area for personalization is determining how frequently sessions should occur. While there is some nomothetic evidence to suggest that more frequent sessions lead to steeper trajectories of improvement, it is likely that this effect may not be as pronounced for all patients given that attending session twice a week may be more burdensome than once a week. Future research should determine which patients will benefit the most from more frequent meetings. Finally, when to terminate treatment also represents a clinical decision point that can be tailored to the individual. More research is necessary to develop data-driven approaches to guide the discontinuation of care.

Despite the limited state of the literature, clinicians should consider combining methods using pretreatment characteristics and routine monitoring to personalize care. Although using patient characteristics to tailor treatment may only more narrowly define the parameters for selecting a one-size-fits-all treatment, data on these characteristics should be collected during intake. Although routine monitoring may be burdensome for the client and clinician, the benefit of catching nonresponders and "off-track" cases early likely exceeds the costs.

As noted previously, the past five decades have witnessed tremendous progress with regard to the identification of evidence-based treatment approaches for a range of mental health conditions. However, data suggest that one-size-fits-all treatment approaches are not sufficient and that data-data driven approaches to personalize treatment (at its outset and throughout its course) are necessary. Clinicians in practice are already making these adaptations, and this article sought to shed light on the empirical status of such decision points.

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