Chapter 13
How, When, and Why Do People Change Through Psychological Interventions?—Patient-Focused Psychotherapy Research

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Introduction

A new clinical idea proposed by a clinical researcher or practicing clinician is—traditionally—the starting point for the development of a new treatment concept. Based on this idea, a new treatment package, comprising a number of interventions, is developed and eventually tested. If these efforts result in preliminary evidence suggesting that this new intervention is effective, the new package and the proposed clinical mechanisms of change are then often disseminated to interested clinicians. However, the evidence base, especially with regard to the actual moderators and mediators of change for psychological interventions, is somewhat limited (Kazdin 2014). The research that actually tests the clinical idea often lags behind and is hardly taken notice of by practicing clinicians. The consequence for the field of psychotherapy is the existence of ubiquitous gap between research and practice. The present chapter deals with an alternative paradigm of treatment development and research, which provides a way to consider the scientist–practitioner gap from both the scientist's as well as the practitioner's perspective (Castonguay et al. 2013). This paradigm is called *patient-focused research*[1] (PFR; Howard et al. 1996; Lutz et al. 2015). While efficacy and effectiveness research are traditionally concerned with the average treatment effect of an established or new treatment approach, PFR is concerned with monitoring actual progress over the course of treatment and providing "real-time" feedback of this information to clinicians (Howard et al. 1996; Lambert 2007; Lambert et al. 2001; Lutz 2002). As such, the pivotal goal of PFR is the use

[1]Patient-focused research (PFR) should be seen synonymous to the expression "patient-oriented research (POR)" used elsewhere in this book, e.g., in Chaps. 1 and 16.

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and implementation of research into the actual treatment process, thereby turning psychotherapy in clinical practice into a truly research-supported intervention. From this point of view, it is not enough that efficacy and effectiveness trials have shown a treatment to be effective on average. Instead, *research support* should be an integral part of each individual's ongoing treatment.

The foregoing chapters have already provided examples of how the ideas of patient-focused research can be implemented in a family therapy context. The present chapter complements these examples with some more empirical and theoretical background. It is important to note that the models discussed in this chapter are not based on a particular approach to psychotherapy. Psychotherapies are considered a class of treatments, defined by overlapping techniques and proposed outcomes. Outcomes are measured by aggregating item scores related to many disorders and complaints. Instead of adapting the treatment only at the beginning by selecting a specific manualized treatment for a respective diagnoses, patient-focused research focuses more on the (real-time) improvement shown in treatment as implemented and the ongoing dynamic adaptation of the treatment based on the progress and the specific needs (dosage and clinical strategies) of the patient (Lutz 2002; Lutz et al. 2015). Therefore, this approach supports a research perspective more focused on outcomes and the improvement of actual clinical practice and less based on a debate about therapeutic schools (e.g., Goldfried 1984; Grawe 1997). Accordingly, the core of this approach requires research to be conducted for individual patients on the course of patient change, in order to learn about differences in patient change as well as subgroups of patients with specific patterns of change.

The chapter is organized into three sections: First, a short overview of dose–response and phase models presents the history and theoretical foundations of patient-focused research. Second, different methods for the generation of decision support tools are described and discussed. Finally, recent research on moderators and mediators of the effects of psychometric feedback are presented, which helps to understand how and for which patients and therapists feedback tools can enhance the effectiveness of psychotherapeutic interventions.

Dose–Response and Phase Models of Therapeutic Change

The theoretical origins of patient-focused psychotherapy research are rooted in the dosage and phase models of psychotherapy. The dosage model of psychotherapeutic effectiveness proposes a negatively accelerating relationship between the number of treatment sessions (dose) and the probability of patient improvement (effect). As such, an increasing number of sessions is associated with diminishing returns in terms of improvement (Howard et al. 1986). In subsequent work, these findings were interpreted as representing rapid improvement early in treatment, while, in later phases, increasing numbers of sessions were necessary to reach a higher percentage of changed patients (Howard et al. 1993; Kadera 1996). Integrating data from 15 studies, Howard et al. (1986) found that after 2 sessions, 30% of the 2431 patients had shown positive results. This percentage increased to 41% after 4 sessions, 53% after 8 sessions, and 75% after 26 sessions. In an extended analysis, Lambert et al. (2001), using more rigorous clinically significant change criteria, showed that these improvement rates were overestimates and were dependent on patients' pretreatment impairment. Using their approach, 50% of patients who were in the dysfunctional range before treatment required 21 sessions to meet clinically significant change criteria. However, for 70% of these patients, more than 35 sessions were necessary to achieve this result. Further research has shown differential change rates for different diagnostic groups and symptom impairment levels (Barkham et al. 1996; Kopta et al. 1994; Maling et al. 1995). Patients who start treatments more severely impaired tend to have more change from pre- to post-treatment but have a lower probability of achieving clinical significant change (Ogles 2013). Also, recent research suggests that change is more rapid in short, time-limited controlled settings than in longer treatments without a predefined end point (Lutz et al. 2015). Lutz et al. (2015) showed that the effects of naturalistic CBT for depression are equal to those reported in the CBT arm of the National Institute of Mental Health Treatment of Depression Collaborative Research Program (NIMH TDCRP; Elkin et al. 1989), if the samples are matched. In the matching variables, several patient intake characteristics were used (symptom severity, dysfunctional attitudes, sex, age, education, and employment status). However, to reach the same BDI outcome scores, CBT in controlled settings needed only about 17 sessions, while, in naturalistic settings, about 35 sessions were provided. Further research using longitudinal assessments is required to reveal how much change in the naturalistic sample had already taken place up until, and how much after, the 17th session.

The question of how much therapy is needed is still an active area of research. An extension and, to some degree, alternative model to the dose–effect model is the good-enough level (GEL; Barkham et al. 1996) of change concept. The GEL model suggests that the diminishing strength of successive sessions (i.e., negatively accelerated/log-linear) is an artifact of aggregating patients with varying treatment lengths. Following the GEL model, patients in routine care stay in treatment until they have reached a level of change that they personally perceive as *good enough*. The path to this individual level might rather be linear than log-linear (Barkham et al. 2006). To test this conjecture, Stulz et al. (2013) separately modeled latent growth curves for patient groups with the same number of treatment sessions. Irrespective of the total amount of treatment sessions, a log-linear model consistently outperformed a linear model supporting the notion of a negatively accelerating change trajectory. Moreover, the dose–effect model is often interpreted as assuming a universal association between the number of sessions and their effects. The GEL model, on the other hand, suggests that the rate of change differs depending on the overall number of sessions attended. That is, patients with shorter treatments should have higher change rates than patients with longer treatments. Meanwhile, this assumption of the GEL model has been supported by several findings (Baldwin et al. 2009; Falkenström et al. 2016; Owen et al. 2016; Reese et al. 2011).

A clinical explanation of the dose–effect relations described above is provided by the phase model. The phase model formulates hypotheses regarding which specific dimensions of outcome change and in which temporal sequence (Howard et al. 1993). Three sequential and progressive phases of the therapeutic recovery process are proposed: (1) remoralization—the enhancement of well-being; (2) remediation—the achievement of symptomatic relief; and (3) rehabilitation—the reduction in maladaptive behaviors, cognitions, and interpersonal problems that interfere with current life functioning. In accordance with the phase model, the decelerating curve of improvement proposed by the dose–effect model can be related to the increasing difficulty of achieving treatment goals in these different domains. This means that well-being is more quickly achieved than symptom change, which, in turn, is achieved more quickly than rehabilitation of life functioning. Moreover, a probabilistic causal relationship between changes in these dimensions is proposed in the phase model. That is, improvement in well-being is assumed to be necessary, but not sufficient, for a reduction in symptom impairment, which, in turn, is assumed to be necessary, but not sufficient for the subsequent amelioration of life functioning. In a study testing the phase model hypothesis, Stulz et al. (2007) identified three patient subgroups on the basis of their development in the respective dimensions (well-being, symptoms, life functioning) over the course of treatment. In each subgroup, well-being increased most rapidly, followed by a reduction in symptoms, while improvements in life functioning were slowest. This finding supports the proposed differential change sensitivity of the three dimensions. Furthermore, about two-thirds of the cases developed in accordance with the predicted temporal sequence of phases (i.e., well-being → symptoms → functioning). However, one-third violated at least one of the two predicted sequences (e.g., moved directly from increased well-being to increased life functioning without a phase of symptom improvement). In addition, results suggested that for more severely distressed patients, the phase model seems to provide a less accurate description of treatment progress. Joyce et al. (2002) reported a similar finding. In light of the earlier findings, further refinement focusing on differential change sequences between individuals is important.

Decision Support Rules

The dosage and phase models conceptualize the process of recovery for an average psychotherapy patient. However, individuals' patterns of improvement can differ significantly from the general trend (Krause et al. 1998). Thus, to take this individuality into account, models are needed that allow the estimation of expected recovery curves for individual patients, based on their progress-relevant pretreatment characteristics. Indeed, this idea was the starting point of patient-focused psychotherapy research (Howard et al. 1996). Patient-focused research asks how well a particular treatment works for the actual treated patient (i.e., whether the patient is benefiting from the treatment they are currently engaged in). The evaluation of treatment progress depends on the idiosyncratic characteristics and developments of the patient with respect to their expected treatment response. For example, minimal progress by session 8 might be insufficient for most patients to consider their treatment a success. However, for a severely impaired patient with a comorbid personality disorder, such moderate progress might be an indicator of a successful intervention (Lutz et al. 2009). As a result, feedback systems designed to support clinical decision-making in psychotherapy should include decision rules allowing the evaluation of treatment progress based on the individual patient's status (e.g., Lambert 2007).

Decision rules can be categorized into two classes (cf. Lambert et al. 2002; Lutz et al. 2006b, 2014b): One approach comprises *rationally derived methods*, which are based on a priori expert judgments about progress in mental health functioning over sessions of psychotherapy. The other approach comprises *empirically derived methods*, which, in contrast, are based on empirically derived expected treatment response (ETR) curves, based on large available data sets of already treated patients.

Rationally Derived Methods

Rationally derived methods make use of psychometric information based on standardized measures for an a priori definition of how much change is necessary to consider a patient improved or recovered. The concept of reliable and clinically significant change is a classic example of rationally derived methods (Jacobson and Truax 1991). This concept comprises two criteria: The first criterion focuses on the actual amount of change achieved by the patient, which must be larger than what would be expected if measurement error were solely responsible for the difference in scores. The measurement error of an instrument depends on its reliability, hence the term reliable change (which comprises both, reliable improvement and also reliable deterioration). The second criterion is fulfilled if a client who was more likely to belong to a patient population before treatment is, at the final assessment, more likely to belong to a non-clinical population (e.g., a community sample). A patient who meets both of these criteria (i.e., improved reliably and crossed the cutoff that separating a clinical from a non-clinical population) is considered clinically significantly improved.

Empirically Derived Methods

Empirically derived methods are based on expected treatment recovery curves generated using data from already treated patients showing similar intake characteristics as the index patient. Additionally, confidence or prediction intervals can be calculated around the predicted change courses. Using this method, it is possible to provide therapists with an estimate of how much their patient's current progress diverges from the expected response curve. Lutz et al. (1999) developed ETR models on the basis of 890 psychotherapy outpatients and identified a set of seven intake variables that significantly predict individual change (e.g., initial impairment, chronicity, previous treatment, patient's expectation of improvement). In an extended study, Lutz et al. (2006a) explored this empirical decision system, varying the size of the prediction interval around each patient's predicted course from 67 to 99.5%. Using this schema, it was shown that the more often a patient's current scores lie outside a confidence interval and the higher the interval, the higher the predictive validity of the current score for ultimate treatment outcome. For instance, as the number of observed values falling below this failure boundary increases (for example between sessions 2 and 8), the probability of treatment failure increases. Vice versa, increasing numbers of observed values above this failure boundary are also associated with a higher probability of treatment success. Thus, the higher the number of positive deviations and the more extreme they are, the higher the probability of treatment success. Similarly, the more frequent and extreme any negative deviations occur (e.g., early in treatment), the higher the probability of treatment failure (Lutz et al. 2006a). These resulting failure/success probabilities can be provided to therapists as a decision support tool. Using this additional information, practitioners can make more empirically informed decisions about whether and how to evaluate and potentially adapt their treatment strategy to enhance the individual patient's outcome. For example, a deviation from the ETR profile in a specific session might result in a "warning" signal to the therapist (and potentially supervisors) or other clinicians involved in the case (e.g., Finch et al. 2001; Lambert et al. 2002; Lueger et al. 2001; Lutz 2002). Different approaches to ETR models have been developed that provide information to help understand individual patient progress. For example, ETR models have been specified for different diagnostic groups or symptom patterns as well as been applied to the study of therapist effects. Furthermore, information about patients' early change has been included to improve these models (e.g., Lutz et al. 2002a, b). Two further extensions are presented in the following: The first concerns a method for the identification of patient subgroups, which helps to generate even more individualized ETR curves. The second concerns adjusting ETRs to different shapes or patterns of patient change.

Nearest Neighbors Techniques

To refine the generation of ETR curves, Lutz et al. (2005) introduced an extended growth curve methodology that applies nearest neighbors (NN) techniques. This approach is based on prediction research from fields other than psychotherapy. In one application, NN are used for the prediction of avalanches (e.g., Brabec and Meister 2001). In this area, large databases with daily-recorded data on potentially relevant parameters (e.g., temperature and barometric pressure) are used to make predictions of avalanche risks on a new day. For this purpose, the 50 (or more) most similar days are selected with respect to the relevant parameters and it is calculated on how many of these similar days an avalanche occurred. This methodology was adapted for the prediction of treatment response by Lutz et al. (2005) in a sample of 203 psychotherapy outpatients seen in the United Kingdom. In accordance with avalanche prediction models, the response curves of the most similar already treated patients (as pendent to the most similar days) are used to derive a prediction for a newly incoming patient. Similarity among patients was defined in terms of Euclidean distances between the relevant predictor variables. Using a sample of 4365 outpatients in the United States, Lutz et al. (2006a) further demonstrated the NN technique to be superior to a rationally derived decision rule with respect to the prediction of the probability of treatment success, failure, and treatment duration using the Outcome Questionnaire (OQ-45; e.g., Lambert 2007). Moreover, Lutz et al. (2006b) tested the predictive validity and clinical utility of the NN approach for differential treatment selection. The authors generated individual predictions for different treatment protocols (cognitive-behavioral therapy [CBT] versus an integrative CBT and interpersonal treatment [IPT] protocol) and compared whether one of these treatments was predicted to be more or less beneficial for a specific patient. Although, on average, no significant difference between the two protocols was found, with the NN method, it was possible to obtain clinically meaningful differential predictions for about one-third of the patients. For the other two-thirds, the predicted change curves did not differ between the two protocols. However, being able to improve treatment selection for one-third of all patients could considerably improve the effectiveness of mental health services and reduce expenses resulting from failed treatments.

Recently, a similar method has been introduced, which aims at treatment selection based on empirical data, namely the Personalized Advantage Index (PAI; DeRubeis et al. 2014; Huibers et al. 2015). Using multiple regression methods that weigh the predictive value of different patient intake characteristics, the PAI is a measure of the potential advantage of a Treatment A over a Treatment B. The use of the PAI has been shown in two applications: In the first demonstration, DeRubeis et al. (2014) used the PAI to predict which patients would profit more from CBT than an antidepressive medication (ADM) and vice versa. In the second study, Huibers et al. (2015) demonstrated the PAI's potential for the selection between cognitive therapy (CT) and IPT. With regard to personalized treatment selection, the ideas behind the NN approach and the PAI are the same. Yet, methodological comparison studies are needed to learn more about their differences and commonalities. A recent extension of both prediction methods could be the integration of data collection during patients' everyday life before the beginning of the treatment (e.g., Fisher 2015; Trull et al. 2012).

Detecting Typical Patterns of Patient Change

By studying different types of psychopathology, psychotherapy research helped to accumulate a large amount of knowledge in terms of specific treatments for particular diagnostic groups (e.g., Barlow 2007). However, considerably less is known about typical patterns of patient change. This situation is stunning given that over the past three decades, outcome research has demonstrated that patient variability is the main source of differences in outcomes (e.g., Lambert 2013; Wampold and Imel 2015). Accordingly, careful examinations of how and when patients improve, or fail to do so, may both increase our understanding of psychotherapy and provide us with tools to improve its effectiveness.

In the last couple of years, this topic emerged in the field of psychotherapy research (e.g., Stulz et al. 2007). Different methodologies that have the potential to reveal meaningful change patterns have been discussed (e.g., Stulz et al. 2007; Tang and DeRubeis 1999). One possibility to extract this kind of information from a collection of individual response curves is pattern recognition procedures such as Growth Mixture Modeling (GMM; e.g., Muthén 2006). GMM clusters patients into subgroups with similar change trajectories on the basis of a latent categorical variable. Thus, it is a form of group-based trajectory modeling that extracts groups of change curves, which develop similarly over time. These kinds of clustering methods already stimulated much research in clinical psychology (cf. Nagin and Odgers 2010). With regard to psychotherapy, GMMs have been used to analyze data from naturalistic settings (Lutz et al. 2007; Rubel et al. 2014, 2015; Stulz and Lutz 2007; Stulz et al. 2007) and from randomized controlled trials (Lutz et al. 2009, 2014a). The most consistently found pattern in the early treatment phase was a subgroup of patients who started severely impaired and improved rapidly (e.g., Rubel et al. 2015). This subgroup of patients is referred to as “early responder”. It has been repeatedly shown that this subgroup of patients has very successful treatments in both naturalistic and controlled settings. The association between early response and treatment duration seems to be dependent on the current setting. While, in naturalistic studies, early response is connected to shorter treatments, in RCTs, it is connected to a higher probability that the patient will complete the number of sessions scheduled in the treatment protocol, i.e., longer treatments (Lutz et al. 2015).

Rationally or Empirically Derived Decision Rules

Several studies investigated the advantages and disadvantages of rationally derived and empirical approaches and yielded mixed results. For example, Lambert et al. (2002) compared a rationally derived method to predict treatment failure with a statistical growth curve technique. The results showed that both methods were relatively equal in their predictions with the empirical approach being somewhat more accurate. Other research also indicates that the empirically derived methods may be slightly superior (e.g., Lutz et al. 2006a; Spielmanns et al. 2006). A recent study compared GMM with clinical significant change criteria to identify early positively responding patients (Rubel et al. 2014). Patients identified in the first three sessions as early responders by means of the GMM method were compared to patients who reliably or clinically significantly improved during the same time period. Generally, GMM categorized many fewer patients as "early positive responders" than the rational methods. Although all of the patients identified via GMM were also identified via the reliable change method and most of the patients were also identified via the clinically significant change method (64%), the group of GMM early positive response patients were shown to be highly specific but insensitive for the prediction of treatment outcome. Consequently, a stepwise approach could use rational clinically significant change criteria as a sensitive screening tool in the first step and, if these criteria are met, the information provided by GMM to increase the specificity of outcome prediction in the second step (Rubel et al. 2015).

Irrespective of the chosen approach (rationally derived or empirical), more research on typical change patterns for subgroups of patients is needed to be able to relate these empirical findings to clinical theories. These theories could be further enhanced by considering related mediators and moderators, which cause different patterns of change and could be used to guide or support clinical decisions (Kazdin 2014). Research on patterns of change is still in its infancy. More studies are necessary to validate and replicate previous findings. However, this research also importantly has the potential to support therapists in their decision-making for each individual patient. For which therapists and patients this information could be especially valuable is discussed in the following section.

Mediators and Moderators of Psychometric Feedback Effects

A large body of research suggests that psychometric feedback and decision rules, such as those described above, are effective for the prevention of treatment failure (e.g., Lambert and Shimokawa 2011). When feedback was additionally complemented with clinical support tools (CST's; Whipple et al. 2003), these effects were even larger. CSTs comprise a special questionnaire for cases that do not develop as positively as expected. Those patients are referred to as "signal clients" as therapists are provided with a red signal so that they are alerted to the increased risk of these patients to have not benefitted at the end of the treatment. This additional questionnaire, the assessment of signal clients (ASC; Lambert et al. 2007), hints at potential problem areas (motivation, alliance, social support, life events, and medication) of this specific patient and accordingly suggests therapists how to tailor their interventions to the needs of these patients.

While most of the early feedback studies were conducted within settings in which relatively short treatments were provided to moderately impaired patients (e.g., college counseling centers; Newnham and Page 2010; Poston and Hansen 2010; Shimokawa et al. 2010), recent studies have investigated feedback effects with more disturbed outpatients (De Jong et al. 2012; Simon et al. 2012), with inpatients (Amble et al. 2015; Byrne et al. 2012; Probst et al. 2013), with patients with eating disorders (Simon et al. 2013), and with patients receiving long-term treatments (>= 35 weeks; De Jong et al. 2014). These more recent investigations generally showed less pronounced feedback effects. Different explanations have been discussed for this reduced effect (Riemer and Bickman 2011; Simon et al. 2012).

Therapist and Patient Differences

A closer look has revealed that feedback is not uniformly effective for every patient and therapist. In a study by Simon et al. (2012), only 50% of the therapists were actually able to use the feedback to substantially improve their clients' outcomes. For the other half of therapists, it made no difference whether or not they received feedback about their patients' progress. Likewise, De Jong et al. (2012) found substantial differences among therapists in the degree to which they profited from a feedback intervention. Female therapists and those with a higher commitment to use the feedback information showed a higher probability of actually using the feedback. The use of feedback, in turn, was associated with being more effective for patients who made less progress than expected (not on-track; NOT). Furthermore, a higher commitment to use the feedback at the beginning of the study was related to more rapidly progressing patients. As a result, therapists seem to have a differential ability of using feedback information for the good of their patients. Underlining another potential factor explaining therapist differences in the context of psychometric feedback, Lutz et al. (2015) found that therapists' as well as patients' attitudes toward and the use of the feedback system were significantly associated with treatment outcome. Especially those therapists who were satisfied with the provided feedback reports and who used the feedback for one specific modification per patient were successful. In another recent study, De Jong and De Goede (2015) investigated factors that influence the attitude formation of therapists toward routine outcome monitoring and feedback. The authors found that a positive attitude toward feedback was associated with a strong prevention focus (i.e., a high motivation to prevent failures) in therapists. This finding suggests that those therapists who are especially eager to receive psychometric progress feedback have a high level of motivation to prevent failures generally. Therefore, efforts with the goal of improving therapists' attitudes toward feedback should especially be designed for those therapists who are motivated by a promotion focus (i.e., high motivation to achieve success).

These therapist differences might in part explain general differences in therapists' ability to successfully provide psychological interventions (e.g., Baldwin and Imel 2013; Lutz and Barkham 2015). Research suggests that about 5–8% of the variability in outcomes is due to therapist differences, depending in part on differences in study design and the impairment of the patient sample (Baldwin and Imel 2013; Saxon and Barkham 2012; Wampold and Brown 2005). It seems that therapist effects are greater for more severely impaired patients and is larger in naturalistic compared to controlled samples (Lutz et al. 2007; Saxon and Barkham 2012). An under-investigated area of research is the question of the impact of therapist effects on treatment length. So far, only one study provides evidence for the existence of substantial differences between therapists with regard to the average length of their treatment (Lutz et al. 2015). In this study, the authors found that about 9% of the differences in treatment length were due to therapists. In an additional analysis, there were also significant therapist differences for patient dropout. However, there was no correlation between the average effectiveness of therapists, the average length of their treatments, and their average dropout rates. That means being an effective therapist with respect to outcome does not mean being effective in terms of dropout or treatment duration. Nevertheless, a comprehensive analysis of therapist effects could help mental health services identify those therapists who might benefit from additional training or supervision. For example, a therapist with a high average effect size but also a high dropout rate might be someone who treats only patients (on purpose or without) for which they are effective and other patients do not stay for some reason with this therapist for very long and drop out.

How Does Feedback Work?

Relatively little evidence is available regarding the question of how feedback works. Investigators in feedback research have devoted considerable energy into predicting treatment non-response (e.g., Lambert et al. 2002; Lutz et al. 2006a; Spielmans et al. 2006) and concluded that the essential value of feedback systems is to help clinicians become aware of pending treatment failure, something that they could not achieve well by means of clinical intuition (e.g., Hannan et al. 2005). In this context, the alarm function is the proposed mechanism by means of which feedback works for NOT cases. That is, feedback hints at negative developments, which therapists might have missed without receiving feedback. However, the findings with regard to therapist differences presented above suggest that it is not this alarm function alone that makes feedback effective. Rather, it seems to be important how therapists use the provided information. In their contextual feedback theory, Sapyta et al. (2005) propose two options if therapists are confronted with negative developments in their patients. In the first option, therapists reduce their commitment to reaching the goal of helping that patient. This is possible by externalizing the reasons for the negative developments to uncontrollable aspects of the patient or context. In this case, the therapist would not change his or her behavior and feedback would not help to improve treatment for the respective patient. If, however, the therapist sticks to his commitment to reach a positive treatment outcome for the patient and believes that they have at least some control over factors that might be associated with failure, then feedback could lead to a behavior change in the therapist. In that case, there is the chance that feedback may help to improve treatment for an individual patient (Sapyta et al. 2005). However, to date, this theory has not been empirically tested.

Another variable that has been proposed as a potential mediator of feedback effects is treatment length. Early feedback studies found that patients with negative feedback (NOT) stayed in treatment longer, while patients with positive feedback (on track; OT) had fewer sessions in comparison with therapies where no feedback was provided (Lambert et al. 2003). This finding suggests that the effects of feedback on treatment outcome might, in part, be mediated by treatment duration. That is, feedback may be effective for NOT patients by informing therapists that these patients need a higher dose of treatment. In turn, this higher dose may lead to better treatment outcomes. However, in more recent studies, the effect of feedback on number of sessions has not been consistently found (Hawkins et al. 2004; Knaup et al. 2009). To date, no study has explicitly tested treatment length as a mediator of feedback effects.

In summary, research on the moderators and mediators of psychometric feedback effects is in a very preliminary stage and most theories hypothesizing how feedback works need more empirical support (Wampold 2015; Amble et al. 2015). Feedback also needs some further development and testing in a variety of settings and environments (e.g., Pinsof et al. 2015). Moreover, more research is needed that investigates and further elaborates CSTs that help clinicians to directly translate psychometric feedback into clinical actions.

Summary

The present chapter provides an overview of patient-focused research, which is the youngest of the three main research paradigms in psychotherapy outcome research. While efficacy and effectiveness research both have a long tradition, PFR was only introduced about 15 years ago. Compared to the traditional paradigms, which focus on the average effects of a treatment, PFR is concerned with the prediction, monitoring, and decision support of individual patients' treatments. Thus, PFR provides individualized empirical support that is designed to inform therapists in the treatment of each of their patients. Technological developments will likely facilitate the implementation of feedback and new adaptive clinical problem-solving tools in the future. These developments might also have an impact on clinical training and supervision (e.g., Castonguay et al. 2013; Emmelkamp et al. 2014; Lambert 2015; Lutz et al. 2015). The more technology develops, the easier it is to implement these feedback and adaptive clinical tools into daily routine and into clinical training. Given that twenty years ago psychotherapy research was limited to a few patients treated in a university setting and assessed in a pre–post design, this new line of research allows us to study psychotherapy in practice, based on large databases, and to immediately integrate this information into the field, while further promoting the integration of science and practice. Thus, the implementation of feedback in the training and supervision of future therapists helps them to build a clinical attitude, which includes psychotherapy research as an integral part of treatment and the clinical identity.

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