VOL 71
ISSUE 3
Summer
2018

THE CLINICAL PSYCHOLOGIST

A publication of the Society of Clinical Psychology (Division 12, APA)

CONTENTS

EDITORIAL STAFF

ISSN 0009-9244

PRESIDENT'S COLUMN

Exploring Theoretical Diversity: A Critical Process for Science

Gary R. VandenBos, Ph.D.

Dialogue between theoretical approaches is critical to the long-term success of any field. This is true for clinical psychology as well. Respect for the clinical models of alternative theories is critical to healthy debate and meaningful research exploration. Being open to understanding the clinical experience of others is essential to building a strong clinical psychology.

There are multiple ways to understand what patients present to us, and there are multiple ways to respond. Which is the best for a given patient, and how do we determine that? The core to a possible answer is to focus on the behavior – the words, the actions, the felt experience described for us by the patient. The reality of their life and their experience. All too often when discussing clinical material with colleagues from different orientations, we discuss them in the "code" of our differing theoretical approaches rather than staying with the concrete specific descriptions presented by the patient. Exposure. The coming APA convention in San Francisco offers each of us a new opportunity to engage with our colleagues in understanding the clinical phenomena regularly presented by our patients in therapy sessions. I strongly encourage each of us to attend at least one clinical session focusing on a topic or patient type of interest that is being presented by someone of a theoretical orientation that differs from our own.

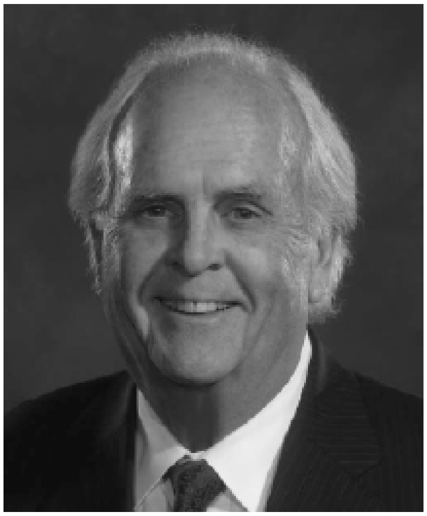
Analyze. Dig through the jargon used in the presentation to the behavioral description by the patients of their words and actions and of those around them. What are the concrete behaviors? What ways of cognitively understanding the words and behavior is the patient using? How are past learning experiences shaping current perceptions and experience? What faulty beliefs are contributing to the difficulties? How would you conceptualize the problem from your perspective? How is the current presenter conceptualizing the problem from their perspective? Can you find a way to discuss the patient and their experience with your colleague that does not involve using the jargon of either of you?

Dialogue. Chat with your colleague after the presentation. Invite them for a "hears" from those words. Explore what each of you would say or do in response (and discuss why). What is important to each of you about the information you would like to learn next from the patient? How would each of you use that information to help the patient to make change in their life? What is the balance for each of you between understanding how the patient got to their present situation and how they can change?

Support Change. Both of you believe in the power of psychotherapy to support, even create, change. Discuss how concretely you would attempt to do that with this patient. Consider whether each of you are now talking within your theoretical model, or whether you are talking within the life experiences and explanatory system of this patient. What explanatory model might be the most effective or useable by this particular patient – to change their behavior, to change their understanding of what is or is not happening in the situation, to change their experience of events so a different response is possible?

Share what you have learned. Maybe the two of you can organize a joint panel together at a future convention. Maybe you can write a manuscript on what you agree on and where your core disagreements lie. Maybe you can design a research project which is a fair test of significant elements related to both of your theoretical approaches. Hopefully you can make a true contribution to the advancement of a more comprehensive understanding in clinical psychology. Enjoy the upcoming convention. Engage with your colleagues, both those who share your views and those who utilize other models. Respect each other. Have a good time.

Congratulations to Division 12 Past President, David H. Barlow, recipient of the 2018 APA/APF Gold Medal Award for Life Achievement in the Practice of Psychology



The APA/APF Gold Medal Award for Life Achievement in the Application of Psychology recognizes a distinguished career and enduring contribution to advancing the professional practice of psychology through a demonstrable effect on patterns of service delivery in the profession. Eligibility is typically limited to psychologists 65 years or older residing in North America. This award is meant to honor colleagues whose career has focused on either the practice of psychology or advancing the practice of psychology.

Here is the official citation for Dr. Barlow:

David H. Barlow has made enormous theoretical and empirical contributions in many areas of clinical psychology. He is the author of more than 600 papers and 80 books, developer of several gold standard interventions for anxiety and related disorders, and editor of several journals. As president of several important professional societies including the Society of Clinical Psychology, he was instrumental in efforts to establish the evidence base of psychological treatments as well as the need to create mechanisms for dissemination of these treatments to the clinic. His career has been a truly remarkable one, and his impact on clinical psychology will be felt for many years to come.

Congratulations Dr. Barlow on this tremendous, and richly deserved, honor!

DIVISION 12 BOARD OF DIRECTORS

SECTION REPRESENTATIVES TO THE DIVISION 12 BOARD

EDITORIAL STAFF

Using Machine Learning Methods to Predict Internalizing Psychopathology Risk and Prognosis

Anthony J. Rosellini, Ph.D.
Center for Anxiety and Related Disorders
Department of Psychological and Brain Sciences
Boston University

A wide range of psychological and environmental factors are associated with the development and course of anxiety, mood, and related disorders (i.e., internalizing disorders). These include (but are not limited to): attentional/cognitive-processing biases (e.g., detection of threat, emotions, Cisler & Koster, 2010), negative thinking styles (e.g., rumination, Nolen-Hoeksema, 2000), personality/temperament (e.g., neuroticism, Zinbarg et al., 2016), childhood experiences (e.g., adversity/trauma, Kessler et al., 2010), and concurrent life stress (Kendler et al., 2010). Coinciding with development of NIMH's Research Domain Criteria, several biologic risk/prognostic factors relevant for internalizing psychopathology also have been identified in recent years. For instance, there is growing evidence that abnormal neurocircuitry (e.g., activation, connectivity, Clauss et al., 2014; Pfleiderer et al., 2014), hypothalamic-pituitary-adrenal axis functioning (e.g., cortisol awakening response, Adam et al., 2014), and electrophysiological responding (e.g., event-related potentials, Meyer, Hajcak, Torpey-Newman, Kujawa, & Klein, 2015; Nelson, Perlman, Klein, Kotov, & Hajcak, 2016) also predict disorder onset and chronicity.

Given the heterogeneity in expressions of internalizing psychopathology and breadth of factors that influence their development and course, researchers are conducting increasingly broad and multi-modal assessments of associated phenotypes and risk/prognostic factors. It is now common for datasets to contain information on hundreds or thousands of potentially important risk/prognostic factors. However, there has been limited effort to fully utilize complex data structures in a single analysis/model. Historically, psychopathology research has evaluated a narrow range or small number of risk/prognostic factors at a time, often relying on parametric statistical methods (e.g., linear/logistic regression) to test circumscribed hypotheses delineated in leading conceptual models. This approach is limited when the goal is to accurately identify exactly who is most likely to develop problematic symptoms, experience a chronic symptom course, or benefit from an empirically-supported treatment. However, technological advances now make it feasible for researchers across disciplines to implement computationally-intense machine learning methods designed to optimize prediction accuracy, and to disseminate complex algorithms via user-friendly app-based interfaces (e.g., using *Shiny*, https://shiny.rstudio.com). Provided below is an overview of (a) the methods used to develop and evaluate prediction tools (i.e., algorithms; risk scores/tools), and (b) the current state of internalizing psychopathology prediction tools.

Anthony J. Rosellini

What is a Prediction Tool?

Prediction tools are intended to accurately identify who is most likely to experience an outcome of interest. Prediction tools assigning values to individuals that represent the expected likelihood (i.e., probability) or degree (i.e., severity) of the outcome. The values are computed based on some weighted combination (e.g., regression coefficients) of personal characteristics that are present prior to the outcome of interest (i.e., risk/prognostic factors). These predicted values subsequently can be used to make specific recommendations for prevention or treatment (e.g., recommending follow-up check-ins or a specific prevention program if deemed "high-risk"). Prediction tools have been developed for a range of health outcomes through federally-funded projects. One example is the atherosclerotic cardiovascular disease risk calculator, developed by the American College of Cardiology and American Heart Association (Goff et al., 2014; see http://static.heart.org/riskcalc/app/index.html#!/baseline-risk). By answering a brief series of questions about socio-demographics and health history (e.g., sex, age, race, cholesterol, blood pressure), this tool provides individuals with their predicted likelihood for having a heart attack or stroke over the next 10 years (e.g., 10% chance). In addition, predicted level of risk is used to make recommendations for interventions that could reduce risk (e.g., starting a statin or hypertension medication).

How are Prediction Tools Developed and Evaluated?

Traditional methods. Although there has been a recent increase in the use of machine learning, most existing prediction tools for health outcomes were developed using conventional (e.g., linear; logistic; survival) regression methods. For example, the most widely used algorithm for 10-year coronary heart disease originally was developed based on coefficients estimated in a Cox proportional hazards model of six established risk factor (i.e., selected a priori; Wilson et al., 1998). When data are available for a large number of risk/prognostic factors, researchers also have used forward or backward stepwise regression in an attempt to identify the best subset(s) of predictors (e.g., Eagle et al., 2004).

Conventional regression methods have limitations when the goal is to utilize all available risk/prognostic factor information to optimize prediction accuracy. Statistical problems arise when several highly correlated predictors are included in a single model (i.e., unstable coefficients/standard errors due to multicollinearity). More specifically, conventional regression methods are prone to *model overfit* (Steyerberg, Eijkemans, & Habbema, 1999), particularly in the presence of multicollinearity (Hastie, Tibshirani, & Friedman, 2009). An overfit model is one that is capturing "noise" in a dataset. Overfit occurs when prediction accuracy is vastly better in the sample used to develop the model (e.g., near perfect prediction) compared to independent/validation samples. In addition to the risk of model overfit, conventional regression methods do not flexibly identify complex interaction (e.g., two-, three-, four-way interactions) among risk/prognostic factors, or nonlinear associations between risk/prognostic factors and the outcome of interest. For example, there are 1,225 possible two-way interactions among a set of 50 potential risk/prognostic variables. Although most interactions might not have associations with the outcome of interest, all 1,225 would have to be constructed and strength/significance of associations evaluated (using a conventional regression framework) to determine if any meaningfully account for variance in the outcome.

Machine learning. Machine learning methods are now being used to develop prediction tools for a wide range of health outcomes (e.g., acute kidney injury, Mohamadlou et al., 2018; 10-year mortality risk score, Rose, 2013). Broadly, machine learning refers to a range of statistical approaches that flexibly "learn" from a dataset. *Supervised* machine learning is used when the goal is to learn how to label (i.e., predict) an output (i.e., outcome/dependent variable) based on a set of input *features* (i.e., predictors/independent variables). Thus, supervised machine learning is used to develop prediction algorithms. A central issue surrounding the use of supervised machine learning is the *bias-variance* tradeoff; fitting a model that is complex and flexible enough to accurately predict an outcome (i.e., minimizing *bias*), but not so complex and flexible that "noise" is used to predict the outcome (i.e., minimizing *variance*/model overfit).

Although there are differences in focus and terminology, traditional psychopathology research methods/statistics have overlap with machine learning methods. Conventional regression methods could be considered a basic form of supervised machine learning (i.e., predicting an outcome), and many introductory machine learning courses first introduce supervised learning using conventional linear and logistic regression as examples. Likewise, *unsupervised* machine learning, which is used to derive structure in a dataset when the output/outcome is unknown or not of concern (e.g., data reduction), also is commonly used in psychopathology research (e.g., principal components analysis; cluster/mixture analysis). Accordingly, there are many relevant applications of machine learning methods in psychopathology research (e.g., identifying fMRI or genetic predictors among thousands of associated measures, Gaiteri, Ding, French, Tseng, & Sibille, 2014; Patel, Khalaf, & Aizenstein, 2016).

There are several broad forms of supervised machine learning, each of which can include many specific approaches to prediction (i.e., different *classifiers*). For example, *regularization* (or *penalization*) methods are an extension of conventional regression that involve shrinking coefficients among sets of collinear predictors to zero (LASSO classifier), toward zero (ridge classifier), or some combination of the two (elastic net classifier), to optimize prediction accuracy while preventing model overfit (Hastie, et al., 2009). *Decision tree* methods exist that recursively partition predictors to automatize the detection/modeling of linear and nonlinear associations between predictors and outcome as well as interactions among predictors (e.g., classification and regression trees classifier, Breiman, Friedman, Olshen, & Stone, 1984; Bayesian additive regression trees classifier, Chipman, George, & McCulloch, 2010; random forests classifier, Breiman, 2001). Regularization and decision-tree methods also can be used to identify optimal subsets of predictors because both provide interpretable output as to how the predictors were utilized in the model (e.g., non-zero LASSO coefficients; random forests variable importance values). *Support vector machines*, in comparison, is more of a "black box" machine learning approach (i.e., predictor coefficients are not estimated) that involves distinguishing different levels of an outcome in the multidimensional space of all available predictors (Cortes & Vapnik, 1995). Importantly, regularization (van Loo, Aggen, Gardner, & Kendler, 2015), decision-trees (Askland et al., 2015), and support vector machines (Koutsouleris et al., 2009) all have been applied in modestly sized samples (i.e., ns = 65-296) to develop accurate internalizing psychopathology prediction algorithms. These methods can be implemented using well-documented R packages (R Core Team, 2015). However, numerous other supervised machine learning methods also exist (e.g., neural nets, Ripley, 1996; see https://cran.r-project.org/web/views/MachineLearning.html). Accordingly, researchers often prioritize and compare several different machine learning classifiers; there is no single "best" approach to supervised machine learning.

Ensemble methods refer to a type of machine learning in which multiple algorithms are consolidated into a single algorithm with improved prediction performance (i.e., improved accuracy or decreased risk of model overfit). Random forests is one of the most commonly used ensemble methods (Breiman, 2001). More specifically, random forests involves generating a single (averaged) decision-tree algorithm from numerous (e.g., 5,000) classification and regression tree (CART) models developed in bootstrapped samples and with a random subsets of available predictors. Using this approach, random forests is less prone to model overfit than a single CART model. However, additional efforts are often necessary to prevent model overfit. Indeed, most machine learning classifiers have several tuning parameters that can influence prediction accuracy and the likelihood of model overfit. Regarding random forests, it may be necessary to limit the maximum tree "length" (e.g., maximum number or size of terminal nodes) to prevent the individual trees from being grown indefinitely (i.e., excessive partitioning of predictors leading to perfect prediction). *Tuning parameters* must be adjusted with careful consideration of the bias-variance tradeoff.

Ensemble machine learning methods also exist to develop algorithms using multiple different approaches to prediction (e.g., conventional regression *and* random forests classifiers). One such method is super learning, which can be used to generate a consolidated algorithm, with optimal mean squared error, using any number of user-specified classifiers (van der Laan, Polley, & Hubbard, 2007). Broadly, super learning involves combining individual-level predictions obtained by different algorithms/classifiers into an optimally weighted average to minimize mean squared error. In other words, super learning can produce a weighted algorithm that simultaneously (a) captures main-terms associations between predictors and an outcome (e.g., using a linear/logistic regression classifier), even if predictors are highly correlated (e.g., using a penalized regression classifier), and (b) detects interactions and nonlinear associations (e.g., using a decision-tree classifier).

Cross-validation is another machine learning approach that is used when concerned with model overfit. The purpose of cross-validation is to test (i.e., validate) how a model might perform in "real world" practice. Typically, prediction algorithms are developed by (a) estimating model coefficients in a *training* or *development* sample (e.g., 75% of the total sample), (b) applying the coefficients in an internal (e.g., 25% of the total sample) or external (i.e., independent) *validation* or *testing* sample to generate predicted values, and (c) evaluating model performance using predicted values from the validation sample (e.g., Briggs, Spencer, Wang, Mannino, & Sin, 2008; Eagle, et al., 2004; Maltoni et al., 1999). In other words, cross-validation involves evaluating prediction accuracy in a group of individuals that is distinct from the group used to develop the model (thus protecting against overfitting when evaluating model performance). In the context of machine learning, *k*-fold cross-validation typically is used both to select optimal tuning parameters (e.g., lambda parametrization for elastic net classifier, Friedman, Hastie, & Tibshirani, 2010) and to estimate model performance. K-fold cross-validation involves dividing a sample into *k* subsamples, fitting the model on k-1 subsets of the subsamples, and applying the model in the remaining $1/k^{th}$ hold-out subsample (i.e., cross-validated predicted values). This process is repeated until cross-validated predicted values are generated for all (mutual exclusive) k hold-out subsamples (i.e., all individuals). Cross-validation methods are more robust than conventional (e.g., 75%/25%) split sample internal validation methods (Harrell, Lee, & Mark, 1996). An advantage of super learning is the default 10-fold cross-validation that is implemented when estimating and assigning the individual-level predicted values for each classifier used to generate the consolidated algorithm.

Evaluating prediction accuracy. Several metrics are used to evaluate the performance of a prediction model (Steyerberg et al., 2010). Although not commonly reported in the prediction tool development literature, one indicator of overall model performance that is frequently reported in clinical psychological research is total variance explained, or R2, with values closer to 1 indicating better model performance. More frequently reported overall performance measures are based on mean model error calculations (e.g., mean absolute error, root mean squared error, Brier score), with values closer to 0 indicating better model performances. For algorithms predicting dichotomous outcomes, measures of discrimination also are reported (and occasionally, calibration). Discrimination refers to the ability of a model to distinguish cases and non-cases. Area under the Receiver Operating Characteristic curve (AUC) reflects overall discrimination, with values ranging from 0 to 1 (<0.50 = prediction no better than chance; 0.50-0.70 = poor prediction; 0.70-0.79 = acceptable prediction; 0.80-0.89 = excellent prediction; >0.90 = outstanding prediction; Hosmer, Lemeshow, & Sturdivant, 2013). AUC is the most common metric used to evaluate accuracy of a prediction model. AUC a calculation of sensitivity (i.e., true positive rate) and 1 - specificity (i.e., 1 - true negative rate; false positive rate) across all possible predicted values. Researchers also often report sensitivity, specificity, and other operating characteristics (e.g., positive/negative predictive value) for specific "high risk" cut-points along the distribution of predicted values (e.g., top 10% of predicted risk).

Internalizing Disorder Prediction Tools

Although efforts have been made to develop prediction tools for mental health outcomes, much of this work has prioritized outcomes related to violence (Ramesh, Igoumenou, Vazquez Montes, & Fazel, 2018; Singh, Grann, & Fazel, 2011), suicide (Cooper et al., 2006; McMillan, Gilbody, Beresford, & Neilly, 2007), and psychosis (Cannon et al., 2016; Carter, Schulsinger, Parnas, Cannon, & Mednick, 2002). Only recently has there been an increase in research aimed at developing prediction tools for internalizing disorders onset and prognosis.

Predicting the development of symptoms. PTSD is one form of internalizing psychopathology for which the development of prediction tools has been prioritized. This is the case because of the vast potential for preventive intervention (Giummarra, Lennox, Dali, Costa, & Gabbe, 2018). A prediction algorithm based on pre-trauma and trauma-specific factors could be used in settings where individuals tend to receive care in the immediate aftermath of trauma exposure (e.g., emergency rooms; disaster relief tents) but before symptoms onset/develop. Although conventional regression methods have been used to develop prediction algorithms for PTSD (e.g., Huang, Tan, Liu, Feng, & Chen, 2010; Russo, Katon, & Zatzick, 2013), most recent studies have utilized machine learning methods. For example, Galatzer-Levy and colleagues (2014) used 10-fold cross-validated support vector machines (SVM) to develop a prediction model for post-traumatic stress symptoms using data from 957 participants admitted to an emergency department because of trauma exposure and who were followed over the subsequent 15 months. The outcome was having a "non-remitting" post-traumatic stress symptom trajectory over the 15 month period, operationalized using latent growth mixture modeling. The predictors included 68 variables representing socio-demographic factors, emergency room assessments (e.g., type of trauma; blood pressure), and acute distress reactions/coping. SVM was used (though other classifiers also were evaluated) to develop a model that predicted non-remitting symptoms with a cross-validated AUC of 0.82 (i.e., excellent prediction). Several subsequent studies have relied on SVM methods to develop prediction algorithms for PTSD outcomes (e.g., Galatzer-Levy, Ma, Statnikov, Yehuda, & Shalev, 2017; Karstoft et al., 2015).

Some studies have used super learning to develop prediction algorithms for PTSD onset (Kessler et al., 2014). Most recently, super learning was used to develop an algorithm predicting post-disaster PTSD from data collected in a prospective survey of Chileans exposed to a highly destructive (8.8 magnitude) earthquake (Rosellini, Dussaillant, Zubizarreta, Kessler, & Rose, 2018). Respondents (*n* = 23,907) were interviewed three months prior to and again three months after the earthquake. Whereas probable PTSD was operationalized using a self-report questionnaire administered in the post-earthquake survey, predictors included 67 self-reported and objective risk factors that could be assessed in the immediate aftermath of an earthquake (e.g., socio-demographics; pre-earthquake health status; ground acceleration in city of residence). Super learning was used to develop a consolidated algorithm from 13 different classifiers (i.e., logistic regression *and* regularization *and* decision trees *and* support vector machines). As expected, the consolidated super learner algorithm had a lower cross-validated mean squared error and better cross-validated AUC than all the individual algorithms from which it was developed. Notably, the super learner achieved a better AUC (0.79) than conventional logistic regression (0.77). Respondents in the top 5%, 10%, and 20% of the cross-validated super learner predicted risk distribution respectively accounted for 17.5%, 32.2%, and 51.4% of all cases of probable PTSD (i.e., sensitivity if top 5%, 10% or 20% were used as the "high risk" cut-point). Positive predictive value, sensitivity, and negative predictive value in these (respective) risk tiers was: 46.6%/96.9%/88.4%; 42.8%/93.4%/90.0%; and 34.2%/84.8%/91.2%). Although the AUC difference of 0.02 reflects a modest improvement in prediction, other studies have found super learning to vastly outperform conventional logistic regression in predicting mental health outcomes (e.g., among soldiers, AUC Δ >.10; Rosellini, Stein, et al., 2018).

In addition to PTSD, preventive interventions have been developed for several other forms of internalizing psychopathology (Sander, Rausch, & Baumeister, 2016; Stockings et al., 2016). Accordingly, research also has attempted to develop algorithms to predict the onset and recurrence of depressive and anxiety disorders. PredictD and PredictA are two of the largest studies to date (King et al., 2006; Moreno-Peral et al., 2014). The goal of PredictD and PredictA were to develop prediction algorithms for major depression, generalized anxiety, and panic disorder that could be used in (European and South American) primary care settings. These projects have developed several prediction tools, relying heavily on traditional regression approaches to algorithm development (King et al., 2013; King et al., 2011; King et al., 2008; Moreno-Peral, et al., 2014). For instance, King and colleagues (2011) used stepwise logistic regression (backwards selection) to develop (n = 4,905) algorithms predicting the onset of a new anxiety diagnosis (i.e., generalized anxiety, panic, other anxiety) over the subsequent 6- or 24- months from 38 potential risk factors (e.g., socio-demographics, prior psychopathology, a range of life stressors). The model achieved acceptable AUCs (0.71-0.81) in three external validation samples. Notably, several similar (secondary) analyses of the National Epidemiologic Survey on Alcohol and Related Conditions (NESARC) dataset have been conducted to develop population-based prediction algorithms for the onset and recurrence (i.e., between Waves 1 and 2) of major depression and panic disorder (Hoertel et al., 2017; Liu, Sareen, Bolton, & Wang, 2015; Wang et al., 2014). The NESARC dataset also has been used to cross-validate the PredictD algorithm for depression onset (Nigatu, Liu, & Wang, 2016).

The extent to which machine learning methods (e.g., super learning) could be used to improve performance of algorithms previously developed using conventional regression methods is unknown. An additional limitation of most algorithms for internalizing psychopathology onset has been the focus *DSM*-based outcomes. There are widely recognized limitations in conceptualizing psychopathology as discrete categorical entities. Accordingly, algorithms are needed to predict transdiagnostic dimensions of internalizing psychopathology rather than discrete disorders as defined in *DSM* (i.e., predicting the development of core underlying processes/features at varying levels of severity rather than disorder presence/absence).

Predicting prognosis. There is also an appeal to developing algorithms that predict internalizing psychopathology course and treatment response (i.e., among individuals with currently problematic symptoms). Individuals predicted to be at risk of having a chronic symptom course might benefit from intensive/combined empirically-supported interventions, whereas individuals most likely to experience a quick/immediate natural remission could be informed that they might not require treatment. Even better, pre-treatment characteristics (e.g., genetics, neural reactivity, personality, comorbid symptoms) could be used to develop algorithms that identify who will receive the most benefit from specific empirically-supported interventions (e.g., predicting who does best with CBT, pharmacotherapy, combined treatment), or benefit equally from any intervention (e.g., supportive therapy). This type of patient-treatment matching is one of the primary goals of precision medicine (Collins & Varmus, 2015).

Several studies have used machine learning methods to develop algorithms that predict the course of internalizing psychopathology in naturalistic and non-randomized clinical samples. Although some studies have focused on longitudinal outcomes for anxiety (e.g., Askland, et al., 2015; Rosellini, Liu, et al., 2018), the vast majority have focused on depression (e.g., Kautzky et al., 2017; Lin et al., 2018; Nie, Vairavan, Narayan, Ye, & Li, 2018). For example, Kessler and colleagues conducted a series of studies in which decision tree and regularization methods were applied to National Comorbidity Survey/World Mental Health Survey data to develop (van Loo et al., 2014; Wardenaar et al., 2014) and validate (Kessler et al., 2016) algorithms predicting depression persistence, chronicity, and severity (e.g., requiring hospitalization) over a 12-year period. Predictors included self-reported family history of depression, temporally primary comorbid disorders, and characteristics of incident depressive episode. The machine learning algorithms achieved acceptable AUCs in the validation sample (0.71–0.76; vs. conventional logistic regression AUC = 0.62–0.70). With regard to sensitivity, 34.6–38.1% of respondents with persistent-chronic depression symptoms and 40.8–55.8% with severe symptoms over follow-up were in the top 20% of the (baseline) predicted risk distribution.

Algorithms that predict differential treatment response are sometimes referred to as “composite moderators” (e.g., Niles et al., 2017) because they represent a weighted composite of several individual predictors of differential treatment response (i.e., capturing multiple two-way interactions between baseline predictors and type of treatment). Several approaches to develop composite moderators have been proposed in recent years (e.g., Kraemer’s moderator profile approach, Kraemer, 2013; DeRubeis’s Personalized Advantage Index, DeRubeis et al., 2014). Although these approaches have been successfully used to develop algorithms predicting differential treatment response (Deisenhofer et al., 2018; Vittengl, Anna Clark, Thase, & Jarrett, 2017), they are based on regression-based methods prone to model overfit and that do not flexibly capture nonlinear associations or complex interactions among predictors. Indeed, limited efforts have been made to integrate machine learning methods in the development of composite moderators (cf. Lorenzo-Luaces, DeRubeis, van Straten, & Tiemens, 2017). Using data from a large RCT (n = 876), for instance, Niles and colleagues (Niles, et al., 2017) implemented the Kraemer approach using stepwise regression and 5-fold cross-validation (but no machine learning method to capture nonlinearities or complex interactions). A composite moderate was developed to assign patients to (a) CBT or medication or both vs. (b) treatment as usual. Ten variables were included in the algorithm (e.g., anxiety sensitivity, depression, sex, education), and the effects of CBT/medication/both were considerably larger when accounting for the composite moderator (d = .34 to .54). The algorithm is freely available online: https://anxiety.psych.ucla.edu/treatmatch.

Summary and Future Directions

There is a clear utility in using machine learning to develop prediction algorithms for internalizing psychopathology outcomes, even in modestly sized samples and when predictors outnumber participant (e.g., Askland, et al., 2015). Over the past five years, machine learning increasingly has been used to develop algorithms predicting the development of internalizing psychopathology. Prediction algorithms for the onset/increase of symptoms could be used to determine who should be followed for additional assessment or recommended for preventive intervention. In addition to trauma and primary care settings, it could be possible to utilize such algorithms during several key life stages/events (for developing psychopathology) and in settings where it is feasible to conduct a risk factor assessment (e.g., college/job orientation; retirement; hospital visit). Given the relatively low (absolute) incidence rates of internalizing psychopathology and likely small effect of prevention on low-risk individuals, new programs could be developed in conjunction with prediction algorithms that identify who is most likely to need or benefit from prevention (cf., recruiting “high risk” participants based on a single measure/cut-score, Buntrock et al., 2016).

Despite the recent emphasis on precision medicine, research focused on predicting differential treatment response has been slower to integrate machine learning methods. However, there is enormous potential. For instance, flexible machine learning classifiers (i.e., capturing nonlinearities and complex interactions) could be integrated with or tested against existing composite moderators. In addition, machine learning methods recently have been developed with the specific intent of predicting optimal treatment for an individual. A combination of super learning and targeted maximum likelihood estimation (van der Laan & Rose, 2011) can be used to develop “optimal treatment rules” that identify which of two treatments will provide the most benefit for an individual based all available pre-treatment covariates (Luedtke & van der Laan, 2017, 2018). One advantage of this methodology is that it can be applied to data from randomized controlled trials *or* naturalistic observational studies to develop the optimal treatment rules (i.e., targeted maximum likelihood estimation is used for causal inference of observational data). Although a thorough baseline assessment and repeated (but brief) follow-up assessments would be needed, using naturalistic patient samples to develop differential treatment response algorithms could be more feasible and generalizable than relying on data collected in randomized control trials (i.e., flexible session frequency; without randomization or strict exclusions). Ψ

References

Adam, E. K., Vrshek-Schallhorn, S., Kendall, A. D., Mineka, S., Zinbarg, R. E., & Craske, M. G. (2014). Prospective associations between the cortisol awakening response and first onsets of anxiety disorders over a six-year follow-up--2013 Curt Richter Award Winner. Psychoneuroendocrinology, 44, 47-59. doi: 10.1016/j.psyneuen.2014.02.014

Askland, K. D., Garnaat, S., Sibrava, N. J., Boisseau, C. L., Strong, D., Mancebo, M., . . . Eisen, J. (2015). Prediction of remission in obsessive compulsive disorder using a novel machine learning strategy. Int J Methods Psychiatr Res, 24(2), 156-169. doi: 10.1002/mpr.1463

Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32.

Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (1984). Classification and Regression Trees. Boca Raton, FL: Chapman & Hall/CRC.

Briggs, A., Spencer, M., Wang, H., Mannino, D., & Sin, D. D. (2008). Development and validation of a prognostic index for health outcomes in chronic obstructive pulmonary disease. Arch Intern Med, 168(1), 71-79. doi: 10.1001/archinternmed.2007.37

Buntrock, C., Ebert, D. D., Lehr, D., Smit, F., Riper, H., Berking, M., & Cuijpers, P. (2016). Effect of a Web-Based Guided Self-help Intervention for Prevention of Major Depression in Adults With Subthreshold Depression: A Randomized Clinical Trial. JAMA, 315(17), 1854-1863. doi: 10.1001/jama.2016.4326

Cannon, T. D., Yu, C., Addington, J., Bearden, C. E., Cadenhead, K. S., Cornblatt, B. A., . . . Kattan, M. W. (2016). An Individualized Risk Calculator for Research in Prodromal Psychosis. Am J Psychiatry, 173(10), 980-988. doi: 10.1176/appi.ajp.2016.15070890

Carter, J. W., Schulsinger, F., Parnas, J., Cannon, T., & Mednick, S. A. (2002). A multivariate prediction model of schizophrenia. Schizophr Bull, 28(4), 649-682.

Chipman, H. A., George, E. I., & McCulloch, R. E. (2010). BART: Bayesian additive regression trees. The Annals of Applied Statistics, 4(1), 266-298.

Cisler, J. M., & Koster, E. H. (2010). Mechanisms of attentional biases towards threat in anxiety disorders: An integrative review. Clin Psychol Rev, 30(2), 203-216. doi: 10.1016/j.cpr.2009.11.003

Clauss, J. A., Avery, S. N., VanDerKlok, R. M., Rogers, B. P., Cowan, R. L., Benningfield, M. M., & Blackford, J. U. (2014). Neurocircuitry underlying risk and resilience to social anxiety disorder. Depress Anxiety, 31(10), 822-833. doi: 10.1002/da.22265

Collins, F. S., & Varmus, H. (2015). A new initiative on precision medicine. N Engl J Med, 372(9), 793-795. doi: 10.1056/NEJMp1500523

Cooper, J., Kapur, N., Dunning, J., Guthrie, E., Appleby, L., & Mackway-Jones, K. (2006). A clinical tool for assessing risk after self-harm. Ann Emerg Med, 48(4), 459-466. doi: 10.1016/j.annemergmed.2006.07.944

Cortes, C., & Vapnik, V. (1995). Support-vector networks. Machine learning, 20(3), 273-297.

Deisenhofer, A. K., Delgadillo, J., Rubel, J. A., Bohnke, J. R., Zimmermann, D., Schwartz, B., & Lutz, W. (2018). Individual treatment selection for patients with posttraumatic stress disorder. Depress Anxiety, 35(6), 541-550. doi: 10.1002/da.22755

DeRubeis, R. J., Cohen, Z. D., Forand, N. R., Fournier, J. C., Gelfand, L. A., & Lorenzo-Luaces, L. (2014). The Personalized Advantage Index: translating research on prediction into individualized treatment recommendations. A demonstration. PLoS One, 9(1), e83875. doi: 10.1371/journal.pone.0083875

Eagle, K. A., Lim, M. J., Dabbous, O. H., Pieper, K. S., Goldberg, R. J., Van de Werf, F., . . . Investigators, G. (2004). A validated prediction model for all forms of acute coronary syndrome: estimating the risk of 6-month postdischarge death in an international registry. JAMA, 291(22), 2727-2733. doi: 10.1001/jama.291.22.2727

Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. Journal of statistical software, 33(1), 1.

Gaiteri, C., Ding, Y., French, B., Tseng, G. C., & Sibille, E. (2014). Beyond modules and hubs: the potential of gene coexpression networks for investigating molecular mechanisms of complex brain disorders. Genes Brain Behav, 13(1), 13-24. doi: 10.1111/gbb.12106

Galatzer-Levy, I. R., Karstoft, K. I., Statnikov, A., & Shalev, A. Y. (2014). Quantitative forecasting of PTSD from early trauma responses: a Machine Learning application. J Psychiatr Res, 59, 68-76. doi: 10.1016/j.jpsychires.2014.08.017

Galatzer-Levy, I. R., Ma, S., Statnikov, A., Yehuda, R., & Shalev, A. Y. (2017). Utilization of machine learning for prediction of post-traumatic stress: a re-examination of cortisol in the prediction and pathways to non-remitting PTSD. Transl Psychiatry, 7(3), e0. doi: 10.1038/tp.2017.38

Giummarra, M. J., Lennox, A., Dali, G., Costa, B., & Gabbe, B. J. (2018). Early psychological interventions for posttraumatic stress, depression and anxiety after traumatic injury: A systematic review and meta-analysis. Clin Psychol Rev, 62, 11-36. doi: 10.1016/j.cpr.2018.05.001

Goff, D. C., Lloyd-Jones, D. M., Bennett, G., Coady, S., D'agostino, R. B., Gibbons, R., . . . O'donnell, C. J. (2014). 2013 ACC/AHA guideline on the assessment of cardiovascular risk: a report of the American College of Cardiology/American Heart Association Task Force on Practice Guidelines. Journal of the American College of Cardiology, 63(25 Part B), 2935-2959.

Harrell, F. E., Jr., Lee, K. L., & Mark, D. B. (1996). Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. Stat Med, 15(4), 361-387. doi: 10.1002/(SICI)1097-0258(19960229)15:4<361::AID-SIM168>3.0.CO;2-4

Hastie, T., Tibshirani, R., & Friedman, J. H. (2009). The elements of statistical learning : data mining, inference, and prediction (2nd ed.). New York: Springer.

Hoertel, N., Blanco, C., Oquendo, M. A., Wall, M. M., Olfson, M., Falissard, B., . . . Limosin, F. (2017). A comprehensive model of predictors of persistence and recurrence in adults with major depression: Results from a national 3-year prospective study. J Psychiatr Res, 95, 19-27. doi: 10.1016/j.jpsychires.2017.07.022

Hosmer, D. W., Lemeshow, S., & Sturdivant, R. X. (2013). Applied logistic regression (Third edition / ed.). Hoboken, New Jersey: Wiley.

Huang, P., Tan, H., Liu, A., Feng, S., & Chen, M. (2010). Prediction of posttraumatic stress disorder among adults in flood district. BMC Public Health, 10, 207. doi: 10.1186/1471-2458-10-207

Karstoft, K. I., Galatzer-Levy, I. R., Statnikov, A., Li, Z., Shalev, A. Y., members of Jerusalem Trauma, O., & Prevention Study, g. (2015). Bridging a translational gap: using machine learning to improve the prediction of PTSD. BMC Psychiatry, 15, 30. doi: 10.1186/s12888-015-0399-8

Kautzky, A., Baldinger-Melich, P., Kranz, G. S., Vanicek, T., Souery, D., Montgomery, S., . . . Kasper, S. (2017). A New Prediction Model for Evaluating Treatment-Resistant Depression. J Clin Psychiatry, 78(2), 215-222. doi: 10.4088/JCP.15m10381

Kendler, K. S., Kessler, R. C., Walters, E. E., MacLean, C., Neale, M. C., Heath, A. C., & Eaves, L. J. (2010). Stressful life events, genetic liability, and onset of an episode of major depression in women. Focus, 8(3), 459-470.

Kessler, R. C., McLaughlin, K. A., Green, J. G., Gruber, M. J., Sampson, N. A., Zaslavsky, A. M., . . . Williams, D. R. (2010). Childhood adversities and adult psychopathology in the WHO World Mental Health Surveys. Br J Psychiatry, 197(5), 378-385. doi: 10.1192/bjp.bp.110.080499

Kessler, R. C., Rose, S., Koenen, K. C., Karam, E. G., Stang, P. E., Stein, D. J., . . . Carmen Viana, M. (2014). How well can post-traumatic stress disorder be predicted from pre-trauma risk factors? An exploratory study in the WHO World Mental Health Surveys. World Psychiatry: Official Journal of the World Psychiatric Association, 13(3), 265-274. doi: 10.1002/wps.20150

Kessler, R. C., van Loo, H. M., Wardenaar, K. J., Bossarte, R. M., Brenner, L. A., Cai, T., . . . Zaslavsky, A. M. (2016). Testing a machine-learning algorithm to predict the persistence and severity of major depressive disorder from baseline self-reports. Mol Psychiatry, 21(10), 1366-1371. doi: 10.1038/mp.2015.198

King, M., Bottomley, C., Bellon-Saameno, J., Torres-Gonzalez, F., Svab, I., Rotar, D., . . . Nazareth, I. (2013). Predicting onset of major depression in general practice attendees in Europe: extending the application of the predictD risk algorithm from 12 to 24 months. Psychol Med, 43(9), 1929-1939. doi: 10.1017/S0033291712002693

King, M., Bottomley, C., Bellon-Saameno, J. A., Torres-Gonzalez, F., Svab, I., Rifel, J., . . . Nazareth, I. (2011). An international risk prediction algorithm for the onset of generalized anxiety and panic syndromes in general practice attendees: predictA. Psychol Med, 41(8), 1625-1639. doi: 10.1017/S0033291710002400

King, M., Walker, C., Levy, G., Bottomley, C., Royston, P., Weich, S., . . . Nazareth, I. (2008). Development and validation of an international risk prediction algorithm for episodes of major depression in general practice attendees: the PredictD study. Arch Gen Psychiatry, 65(12), 1368-1376. doi: 10.1001/archpsyc.65.12.1368

King, M., Weich, S., Torres-Gonzalez, F., Svab, I., Maaroos, H. I., Neeleman, J., . . . Nazareth, I. (2006). Prediction of depression in European general practice attendees: the PREDICT study. BMC Public Health, 6, 6. doi: 10.1186/1471-2458-6-6

Koutsouleris, N., Meisenzahl, E. M., Davatzikos, C., Bottlender, R., Frodl, T., Scheuerecker, J., . . . Gaser, C. (2009). Use of neuroanatomical pattern classification to identify subjects in at-risk mental states of psychosis and predict disease transition. Arch Gen Psychiatry, 66(7), 700-712. doi: 10.1001/archgenpsychiatry.2009.62

Kraemer, H. C. (2013). Discovering, comparing, and combining moderators of treatment on outcome after randomized clinical trials: a parametric approach. Stat Med, 32(11), 1964-1973. doi: 10.1002/sim.5734

Lin, E., Kuo, P. H., Liu, Y. L., Yu, Y. W., Yang, A. C., & Tsai, S. J. (2018). A Deep Learning Approach for Predicting Antidepressant Response in Major Depression Using Clinical and Genetic Biomarkers. Front Psychiatry, 9, 290. doi: 10.3389/fpsyt.2018.00290

Liu, Y., Sareen, J., Bolton, J., & Wang, J. (2015). Development and validation of a risk-prediction algorithm for the recurrence of panic disorder. Depress Anxiety, 32(5), 341-348. doi: 10.1002/da.22359

Lorenzo-Luaces, L., DeRubeis, R. J., van Straten, A., & Tiemens, B. (2017). A prognostic index (PI) as a moderator of outcomes in the treatment of depression: A proof of concept combining multiple variables to inform risk-stratified stepped care models. Journal of affective disorders, 213, 78-85.

Luedtke, A. R., & van der Laan, M. J. (2017). Evaluating the impact of treating the optimal subgroup. Statistical methods in medical research, 26(4), 1630-1640.

Luedtke, A. R., & van der Laan, M. J. (2018). Optimal Dynamic Treatment Rules Targeted Learning in Data Science (pp. 399-417): Springer.

Maltoni, M., Nanni, O., Pirovano, M., Scarpi, E., Indelli, M., Martini, C., . . . Amadori, D. (1999). Successful validation of the palliative prognostic score in terminally ill cancer patients. Italian Multicenter Study Group on Palliative Care. J Pain Symptom Manage, 17(4), 240-247.

McMillan, D., Gilbody, S., Beresford, E., & Neilly, L. (2007). Can we predict suicide and non-fatal self-harm with the Beck Hopelessness Scale? A meta-analysis. Psychol Med, 37(6), 769-778. doi: 10.1017/S0033291706009664

Meyer, A., Hajcak, G., Torpey-Newman, D. C., Kujawa, A., & Klein, D. N. (2015). Enhanced error-related brain activity in children predicts the onset of anxiety disorders between the ages of 6 and 9. J Abnorm Psychol, 124(2), 266-274. doi: 10.1037/abn0000044

Mohamadlou, H., Lynn-Palevsky, A., Barton, C., Chettipally, U., Shieh, L., Calvert, J., . . . Das, R. (2018). Prediction of Acute Kidney Injury With a Machine Learning Algorithm Using Electronic Health Record Data. Can J Kidney Health Dis, 5, 2054358118776326. doi: 10.1177/2054358118776326

Moreno-Peral, P., Luna Jde, D., Marston, L., King, M., Nazareth, I., Motrico, E., . . . Bellon, J. A. (2014). Predicting the onset of anxiety syndromes at 12 months in primary care attendees. The predictA-Spain study. PLoS One, 9(9), e106370. doi: 10.1371/journal.pone.0106370

Nelson, B. D., Perlman, G., Klein, D. N., Kotov, R., & Hajcak, G. (2016). Blunted Neural Response to Rewards as a Prospective Predictor of the Development of Depression in Adolescent Girls. Am J Psychiatry, 173(12), 1223-1230. doi: 10.1176/appi.ajp.2016.15121524

Nie, Z., Vairavan, S., Narayan, V. A., Ye, J., & Li, Q. S. (2018). Predictive modeling of treatment resistant depression using data from STAR*D and an independent clinical study. PLoS One, 13(6), e0197268. doi: 10.1371/journal.pone.0197268

Nigatu, Y. T., Liu, Y., & Wang, J. (2016). External validation of the international risk prediction algorithm for major depressive episode in the US general population: the PredictD-US study. BMC Psychiatry, 16, 256. doi: 10.1186/s12888-016-0971-x

Niles, A. N., Loerinc, A. G., Krull, J. L., Roy-Byrne, P., Sullivan, G., Sherbourne, C. D., . . . Craske, M. G. (2017). Advancing Personalized Medicine: Application of a Novel Statistical Method to Identify Treatment Moderators in the Coordinated Anxiety Learning and Management Study. Behav Ther, 48(4), 490-500. doi: 10.1016/j.beth.2017.02.001

Nolen-Hoeksema, S. (2000). The role of rumination in depressive disorders and mixed anxiety/depressive symptoms. J Abnorm Psychol, 109(3), 504-511.

Patel, M. J., Khalaf, A., & Aizenstein, H. J. (2016). Studying depression using imaging and machine learning methods. Neuroimage Clin, 10, 115-123. doi: 10.1016/j.nicl.2015.11.003

Pfleiderer, B., Berse, T., Stroux, D., Ewert, A., Konrad, C., & Gerlach, A. L. (2014). Internal focus of attention in anxiety-sensitive females up-regulates amygdale activity: an fMRI study. J Neural Transm (Vienna), 121(11), 1417-1428. doi: 10.1007/s00702-014-1248-5

R Core Team. (2015). R: A language and environment for statistical computing. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from https://www.R-project.org/

Ramesh, T., Igoumenou, A., Vazquez Montes, M., & Fazel, S. (2018). Use of risk assessment instruments to predict violence in forensic psychiatric hospitals: a systematic review and meta-analysis. Eur Psychiatry, 52, 47-53. doi: 10.1016/j.eurpsy.2018.02.007

Ripley, B. D. (1996). Pattern recognition and neural networks. Cambridge ; New York: Cambridge University Press.

Rose, S. (2013). Mortality risk score prediction in an elderly population using machine learning. Am J Epidemiol, 177(5), 443-452. doi: 10.1093/aje/kws241

Rosellini, A. J., Dussaillant, F., Zubizarreta, J. R., Kessler, R. C., & Rose, S. (2018). Predicting posttraumatic stress disorder following a natural disaster. J Psychiatr Res, 96, 15-22. doi: 10.1016/j.jpsychires.2017.09.010

Rosellini, A. J., Liu, H., Petukhova, M. V., Sampson, N. A., Aguilar-Gaxiola, S., Alonso, J., . . . Kessler, R. C. (2018). Recovery from DSM-IV post-traumatic stress disorder in the WHO World Mental Health surveys. Psychol Med, 48(3), 437-450. doi: 10.1017/S0033291717001817

Rosellini, A. J., Stein, M. B., Benedek, D. M., Bliese, P. D., Chiu, W. T., Hwang, I., . . . Kessler, R. C. (2018). Predeployment predictors of psychiatric disorder-symptoms and interpersonal violence during combat deployment. Depress Anxiety. doi: 10.1002/da.22807

Russo, J., Katon, W., & Zatzick, D. (2013). The development of a population-based automated screening procedure for PTSD in acutely injured hospitalized trauma survivors. Gen Hosp Psychiatry, 35(5), 485-491. doi: 10.1016/j.genhosppsych.2013.04.016

Sander, L., Rausch, L., & Baumeister, H. (2016). Effectiveness of Internet-Based Interventions for the Prevention of Mental Disorders: A Systematic Review and Meta-Analysis. JMIR Ment Health, 3(3), e38. doi: 10.2196/mental.6061

Singh, J. P., Grann, M., & Fazel, S. (2011). A comparative study of violence risk assessment tools: a systematic review and metaregression analysis of 68 studies involving 25,980 participants. Clin Psychol Rev, 31(3), 499-513. doi: 10.1016/j.cpr.2010.11.009

Steyerberg, E. W., Eijkemans, M. J., & Habbema, J. D. (1999). Stepwise selection in small data sets: a simulation study of bias in logistic regression analysis. J Clin Epidemiol, 52(10), 935-942.

Steyerberg, E. W., Vickers, A. J., Cook, N. R., Gerds, T., Gonen, M., Obuchowski, N., . . . Kattan, M. W. (2010). Assessing the performance of prediction models: a framework for traditional and novel measures. Epidemiology, 21(1), 128-138. doi: 10.1097/EDE.0b013e3181c30fb2

Stockings, E. A., Degenhardt, L., Dobbins, T., Lee, Y. Y., Erskine, H. E., Whiteford, H. A., & Patton, G. (2016). Preventing depression and anxiety in young people: a review of the joint efficacy of universal, selective and indicated prevention. Psychol Med, 46(1), 11-26. doi: 10.1017/S0033291715001725

van der Laan, M. J., Polley, E. C., & Hubbard, A. E. (2007). Super learner. Statistical Applications in Genetics and Molecular Biology, 6, Article25. doi: 10.2202/1544-6115.1309

van der Laan, M. J., & Rose, S. (2011). Targeted Learning: Causal Inference for Observational and Experimental Data. New York: Springer.

van Loo, H. M., Aggen, S. H., Gardner, C. O., & Kendler, K. S. (2015). Multiple risk factors predict recurrence of major depressive disorder in women. J Affect Disord, 180, 52-61. doi: 10.1016/j.jad.2015.03.045

van Loo, H. M., Cai, T., Gruber, M. J., Li, J., de Jonge, P., Petukhova, M., . . . Kessler, R. C. (2014). Major depressive disorder subtypes to predict long-term course. Depress Anxiety, 31(9), 765-777. doi: 10.1002/da.22233

Vittengl, J. R., Anna Clark, L., Thase, M. E., & Jarrett, R. B. (2017). Initial Steps to inform selection of continuation cognitive therapy or fluoxetine for higher risk responders to cognitive therapy for recurrent major depressive disorder. Psychiatry Res, 253, 174-181. doi: 10.1016/j.psychres.2017.03.032

Wang, J. L., Patten, S., Sareen, J., Bolton, J., Schmitz, N., & MacQueen, G. (2014). Development and validation of a prediction algorithm for use by health professionals in prediction of recurrence of major depression. Depress Anxiety, 31(5), 451-457.

Wardenaar, K. J., van Loo, H. M., Cai, T., Fava, M., Gruber, M. J., Li, J., . . . Kessler, R. C. (2014). The effects of co-morbidity in defining major depression subtypes associated with long-term course and severity. Psychol Med, 44(15), 3289-3302. doi: 10.1017/S0033291714000993

Wilson, P. W., D'Agostino, R. B., Levy, D., Belanger, A. M., Silbershatz, H., & Kannel, W. B. (1998). Prediction of coronary heart disease using risk factor categories. Circulation, 97(18), 1837-1847.

Zinbarg, R. E., Mineka, S., Bobova, L., Craske, M. G., Vrshek-Schallhorn, S., Griffith, J. W., . . . Anand, D. (2016). Testing a hierarchical model of neuroticism and its cognitive facets: latent structure and prospective prediction of first onsets of anxiety and unipolar mood disorders during 3 years in late adolescence. Clinical Psychological Science, 4(5), 805-824.

SCP Member Spotlight on Teresa Leyro, Ph.D.

Dr. Teresa Leyro is an exceptionally productive, collaborative, and collegial early career psychologist. She has already published over 30 peer-reviewed journal articles; she is an active leader within Division 12 (SCP) including chairing the Continuing Education Sub-Committee; and she is an excellent role model for early career professionals as well as students pursuing an academic/research career. We had the opportunity to learn more about Dr. Leyro and her work through our Q&A correspondence over the past month. Read on to learn more!

Where did you complete your training?

I completed my doctoral studies in the Clinical Psychology Program at the University of Vermont, including a clinical internship at University of California, San Francisco. I completed a postdoctoral fellowship at the University of California, San Francisco.

What is your current position and what are your research interests?

I'm an Assistant Professor in the Clinical Program of the Department of Psychology at Rutgers, The State university of New Jersey. My research focuses on the roles of cognitive-affective and biological vulnerability factors in the etiology and maintenance of substance use disorders, with a particular focus on the comorbidity among anxiety, stress, and tobacco dependence. My translational research program aims to inform the development and subsequent testing of novel adjunctive interventions.

In addition to my roles in SCP, I am also a member of the Society for Research on Nicotine and Tobacco where I am on the Membership Committee and I'm an active member of the BRIDGE (Building Roads to Inclusion and Diversity in Graduate Education) network.

Teresa Leyro

What's something nobody would know about you?

I have tap danced for most of my life. When I applied to graduate school I made myself a deal that if I did not get in, I would take a year off to focus on dance and audition to be a Rockette.

What led to your interest in clinical psychology?

I've always loved psychology but as an undergraduate, I was not focused squarely on clinical science, per se. However, one of the final projects I completed in an applied course was the development of a personalized smoking cessation intervention for my father. It was grounded in basic behavioral principles. Unbeknownst to me at the time, this early project seems to have accurately forecast the work in which I'm currently engaged.

What do you see as an important direction for the field of Psychology?

From an applied perspective, I am enthusiastic about the progress I am seeing in integrated health care and behavioral medicine. As a researcher, I am excited about opportunities to collaborate across different specializations to promote better translation of work from bench to bedside, as well as building integrative programs of work both within psychology and across other science and technology fields. While I see great progress in these areas, the increasingly limited time and resources threaten progress. We need to be more creative as researchers and also demand greater support at the institutional, state, and federal levels in order to pursue these activities.

SCP Member News

The Membership Committee is pleased to share the extraordinary accomplishments and ongoing contributions made by SCP members to the field of Clinical Psychology.

Walter Penk, Ph.D., ABPP

Dr. Walter Penk received the 2018 Alfred M. Wellner Lifetime Achievement Award from the National Register of Health Service Psychologists. The award is the highest honor bestowed on a Registrant by the National Register to commemorate numerous and significant contributions to psychology during a distinguished career. Dr. Penk was selected based on his many achievements including his extensive work researching treatments for Posttraumatic Stress Disorder, lifetime of service to the VA, leadership in developing and implementing innovative treatments for Veterans, and the supervision and mentorship he has provided to a generation of clinicians. Dr. Penk currently holds the position of Professor at the Texas A&M College of Medicine and is a Consultant to the Department of Veterans Affairs VISN 17 Center of Excellence and the Bedford VA Medical Center. Dr. Penk also recently co-edited the Second Edition of Treating PTSD Among Military Personnel (Guilford, in press).

Elliot Jurist, Ph.D.

Dr. Elliot Jurist is a full professor of psychology and philosophy at the City College of New York and the Graduate Center of the City University of New York (CUNY). Dr. Jurist was also formerly the Director of the Doctoral Program in Clinical Psychology and served as Editor of Psychoanalytic Psychology for 10 years. Dr. Jurist is an expert on emotion regulation, specifically the process of mentalization, and recently published Minding Emotions: Cultivating Mentalization in Psychotherapy (Guilford). This book expands on a new model of emotion regulation in psychopathology developed by Dr. Jurist and his colleague, along with a self-report questionnaire called the Mentalization Affectivity Scale (MAS). Dr. Jurist and his colleagues are conducting research on the model and the measure in the United States, Germany, Turkey, Spain, and Korea.

Katherine Dixon-Gordon, Ph.D.

DDr. Katherine Dixon-Gordon received the 2018 Judy E. Hall, PhD, Early Career Psychologist Award from the National Register of Health Service Psychologists. Dr. Dixon-Gordon was selected based on her exceptional achievements as an Early Career Psychologist and proposal to use the award stipend to fund research to better understand the gap between patients who need care and those who receive it, with a focus on care provision to patients with psychological and substance use disorders in emergency departments. Her project will recruit emergency room providers and, using an experimental paradigm, examine the effect of the presence or absence of patient co-occurring psychological disorders on the quality of care (e.g., referrals provided) using hypothetical vignettes. Potential barriers to receiving care and referrals will also be examined, including access to institutional resources, past training in intervention and effective treatments for psychological disorders, and negative attitudes.

Joel Block, Ph.D., ABPP

Dr. Joel Block is board certified in couple therapy by the American Board of Professional Psychology, a Fellow of APA Division 43 (Society for Couple and Family Psychology), a senior psychologist on the staff of the Northwell Health System, and an Assistant Clinical Professor (Psychology/Psychiatry) at the Hofstra Northwell School of Medicine. Dr. Block has authored over 20 books, including three published this year. *Love Affairs: The Therapeutic Guide to Sound Thinking and Smart Moves After Infidelity* (Praeger) is an academic book combining the latest research and clinical experience on treating infidelity. *The 15-Minute Relationship Fix* (Koehler) is a clinically developed strategy for repairing and strengthening relationships. *The Love Manual* is an innovative approach that combines identification of key genetic factors for couples with research-based psychological compatibility instrument. The book provides individualized suggestions for bridging emotional and behavioral differences based on genetic and psychological differences.

Please submit nominations to:

Members in the News: https://www.div12.org/members-in-the-news/

Considerations in the Development of Professionalism

Michelle S. Schultz, Psy.D.

Wright State University

Every profession, including psychology, has a unique culture defined by the individual and group values, beliefs, attitudes, customs, and behaviors associated with it. One's ability to assimilate into this culture is conceptualized as their professionalism. In the field of psychology, factors that have been associated with professionalism include the development of a professional identity (e.g., thinking like a psychologist), evidencing behavior and comportment that reflect the values and attitudes of psychology, refining interpersonal and self-reflective skills as defined by the profession, and internalizing standards of the profession (e.g., ethics, diversity) (American Psychological Association, 2011; Elman, Illfelder-Kaye, & Robiner, 2005). The evolution of professional cultures reflects historic and socio-cultural factors (e.g., social class and gender issues), as such, professionalism and professional credibility have historically been defined by middle- to upper-class white male values and norms which may disadvantage those who do not fit the "professional ideal" (Adamson & Johansson, 2016; Hall, 2005).

Graduate education and mentoring of early career psychologists (ECP) typically focuses on both the development of skills related to the profession's specified work-functions and professionalism. Students and ECPs are taught not only what to do, but also how to "think and act like" others within psychology. Students and ECPs are frequently evaluated by their knowledge of and how well they ascribe to psychology's professionalism. However, consideration for the individual's intersectional identities and diversity context (e.g., social class, gender, race, ethnicity, sexual orientation, and ability) and/or previous exposure to professionalism (i.e., status as first-generation student/professional) and the historical context/cultural underpinnings of professionalism is not always taken into consideration when professional development activities or evaluations are undertaken. By not considering the influence of culture and context on the definition and evaluation of professionalism within psychology, certain individuals and/or groups may be excluded from and/or devalued within the field.

As colleagues, educators, supervisors, and mentors, it is crucial to consider how professionalism evolved within psychology as well as how socialization into the profession is conducted and impacts the individual. For example, ensuring feedback on "professional dress" takes into consideration cultural norms and financial means of the individual along with appropriateness for the practice setting and historically defined appropriate attire. Psychologists need to be mindful of where their own backgrounds are represented in the historical culture of the profession and how that can potentially serve to marginalize individuals from differing backgrounds. In addition, it is important to consider how to support diversity within the profession and serve as allies and advocates in creating an inclusive professional culture and conceptualization of professionalism.

References

Adamson, M., & Johansson, M. (2016). Compositions of professionalism in counselling work: An embodied and embedded intersectionality framework. Human Relations, 69(12), 2201-2223.

American Psychological Association, Task Force on the Assessment of Competence in Professional Psychology. (2011). Revised Competency Benchmarks for Professional Psychology. Retrieved from http://www.apa.org/ed/graduate/competency.aspx

Elman, N. S., Illfelder-Kaye, J., & Robiner, W. N. (2005). Professional development: Training for professionalism as a foundation for competent practice in psychology. Professional Psychology: Research and Practice, 4, 367-375.

Hall, P. (2005). Interprofessional teamwork: Professional cultures as barriers. Journal of Interprofessional Care, 1, 188-196.

Ethical Considerations for New Psychologists

Adam L. Fried, Ph.D.
Kate L. Jansen, Ph.D.
Midwestern University

This past summer, many clinical psychology students and postdocs fulfilled their educational requirements and will begin careers as independent psychologists. Although training and supervised experience provide indispensable preparation for careers in psychology, the experience of being an independent practitioner is itself an education in what it truly means to be a professional.

Many questions common among new psychologists result from an understandable unfamiliarity with their new role as an independent professional. While many have received quality mentoring in many of the professional activities, such as intervention and assessment, few are prepared for the some of the "real world" ethical dilemmas they may encounter. We thought it might be helpful to discuss some questions we frequently hear from advanced students and interns preparing for independent practice. The purpose is not to provide an exhaustive discussion of each topic but rather to highlight some important questions frequently encountered by new professionals and provide some general guidance in terms of how ethics-related concepts, resources and tools may help inform responsible decision-making.

Should I accept any client/patient who asks for my services? What do I do if a client is no longer benefitting from my services?

One of the most important professional challenges for early career professionals may be determining criteria for accepting and terminating with clients. For example, some interns and early career professionals are surprised when told that they are not, in fact, required to accept every client who seeks their service. The question of whether to accept a client has less to do with whether the client thinks you are the "perfect psychologist" and more to do with whether, based upon your training and experience, you would be able to provide effective services for the client [see American Psychological Association (APA) Ethics Code standards 2.01 Boundaries of Competence and 3.04 Avoiding Harm, APA, 2017]. Some clinicians incorrectly reason that they could accept clients simply because "The person really wanted me to treat them" and "I'm just starting out and I really need clients." While we are sympathetic to fears of disappointing others or the financial pressures associated with independent practice, these are problematic reasons for accepting clients.

Similarly, termination may be an area of confusion for many early career psychologists, especially in terms of determining when termination is appropriate and developing practices consistent with ethical and legal responsibilities and responsive to client needs (see Davis and Younggren, 2009 for a discussion of recommended practices). Many clinicians have difficulty distinguishing "termination" (see Standard 10.10 Terminating Therapy, APA, 2017) from "abandonment" (Younggren, 2011), with the latter defined as "the failure of the psychologist to take the clinically indicated and ethically appropriate steps to terminate a professional relationship" (Younggren & Gottlieb, 2008, p. 500). While many psychologists may be hesitant to terminate treatments with clients who are no longer benefitting due to fears of abandonment, they often do not consider the risks of not addressing termination, namely, providing treatments when the client/patient is not likely to benefit.

If I'm not being supervised, what resources will I have to resolve ethical dilemmas?

Peer consultation and peer consultation groups are an excellent resource for continued professional growth, as well as a check on professional and clinical ethical concerns that arise in independent practice. Despite gaining popularity and recognition of importance, many early career professionals remain uncertain how to start or join a peer consultation group or may not realize how peer consultation can help their practice. Peer consultation can be a valuable tool for all practicing psychologists; this holds particularly true for early career psychologists making the transition from supervised to independent practice. Consultation with colleagues is encouraged in the APA Ethics Code (2017) and in other jurisdictions, is a requirement for independent practice. For example, the Psychology Board of Australia requires 10 hours of "supervision and consultation in individual or group format, for the purposes of professional development and support in the practice of psychology and includes a critically reflective focus on the practitioner's own practice" for licensed psychologists (Psychology Board of Australia, 2015, p. 23).

In addition to utilizing peers for consultation on ethical dilemmas, early career psychologists have access to many professional organization resources. The APA Ethics Office offers educational resources on the interpretation and implementation of the APA Ethics

Code. Many state psychology associations have ethics consultations or ethics committees available for consultation in the case of questions or dilemmas. Professional insurance carriers also offer consultations for members with ethical or risk management questions. In cases where peer consultation seems insufficient, utilizing these professional resources may help provide clarity to the concern or dilemma at hand.

Regardless of the resource utilized, documentation is essential. Though we are well versed on the importance of documenting clinical encounters, it is not always intuitive to document the steps taken to address ethical concerns as they arise. An easy-to-remember method of consultation documentation focuses on the "who", "what", "when", "where", and "why" of what occurred (Suttle, 2018). This would include who you spoke with (in the case of peer consultation, if the group members have agreed to this), what the concern was, when this discussion occurred, the type of consultation to obtained (peer, professional, other), and why you did or did not take a specified action.

How do I manage electronic and other boundaries with clients?

Most students are aware of major boundary issues such as APA Ethics Code (APA, 2017) prohibitions against sexual relationships with clients (Standard 10.05) and relatives of clients (Standard 10.06) but many are not as familiar with how to handle other types of boundary crossings. Some common dilemmas include how to handle interactions via social media, unanticipated encounters outside of professional interactions, and client requests that may lead to difficult ethical situations and put the therapist at legal and/or ethical risk (see Standard 3.05 Multiple Relationships; APA, 2017). New clinicians may lack experience in terms of how to effectively handle these situations or even incorrectly assume that the client bears the responsibility as the initiator of the request.

An emerging ethics questions for new (and experienced) psychologists has to do with boundaries on the Internet, such as the ethics of searching for client information. A survey by Kolmes and Taube (2014) revealed that almost half of mental health professionals surveyed searched online for information about clients. Doctoral students may be even more likely to conduct searches; a survey by DiLillo and Gale (2011) found that nearly 98% had searched for client information using the Internet and 94% reported that they searched for client information on social networking sites. There may also be considerable concern about clients finding personal information about clinicians on the Internet. Kolmes and Taube conducted a second study (2016) with individuals receiving therapy services and found that approximately 60% had intentionally sought personal information about their therapist online, including information about their family, photos and home address. Intentional clinician-initiated searches can be ethically problematic for several reasons. Many (e.g., Kaslow, Patterson & Gottleib, 2011) have argued that web searches of client information (in non-emergency situations and without the knowledge of the client) may violate the client's trust and reasonable expectations for privacy, and has the potential to hinder the professional relationship.

In an age when electronic communication is sometimes more common that telephone or face-to-face methods, it can be confusing (to say the least) to develop policies that both serve the needs of your clients while adhering to professional regulations and maintaining appropriate boundaries. Ethical quandaries (in addition to awkward situations, misunderstandings and hurt feelings) can often be prevented through clear policies and informed consent discussions. For example, many clinicians now include written policies (both on their website and in informed consent documents) on whether they engage in and the parameters surrounding the use of texting, email, and communication on social media.

Conclusion:

Becoming an independent psychologist marks an exciting professional milestone. Having the power to develop policies and make decisions for oneself, rather than following the directives of a supervisor, can be both exhilarating but also daunting. We briefly highlighted some frequently encountered questions that new psychologists may find challenging but realize that these are difficult questions for professionals of all experience levels, as there are seldom clear-cut answers. Although proper planning can help prevent some difficult ethical situations, psychologists will undoubtedly encounter dilemmas for which they did not anticipate or prepare. Some tenets of ethical decision-making that we have found helpful to keep in mind that we've tried to illustrated throughout this column include maintaining a commitment to fulfilling professional responsibilities (rather than personal interests), actively seeking out knowledge of applicable regulations and laws that may inform the decision, consulting and generating possible solutions, and documenting appropriately. Ψ

References

American Psychological Association (2017). Ethical principles of psychologists and code of conduct (Amended January 1, 2017). Retrieved July 12, 2018 from http://www.apa.org.ethics

Davis, D.D. & Younggren, J.N. (2009). Ethical competence in psychotherapy termination. Professional Psychology: Research and Practice, 40(6), 572-578.

DiLillo, D., & Gale, E.B. (2011). To Google or not to Google: Graduate students' use of the Internet to access personal information about clients. Training and Education in Professional Psychology, 5(3), 160-166.

Kaslow, F.W., Patterson, T., Gottlieb, M. (2011). Ethical dilemmas in psychologists accessing Internet data: Is it justified? Professional Psychology: Research and Practice, 42(2), 105-112.

Kolmes, K., & Taube, D.O. (2014). Seeking and finding our clients on the Internet: Boundary considerations in Cyberspace. Professional Psychology: Research and Practice, 45(1), 3-10.

Kolmes, K., & Taube, D.O. (2016). Client discovery of psychotherapist personal information online. Professional Psychology: Research and Practice, 47(2), 147-154.

Psychology Board of Australia (2015). Guidelines on continuing professional development. Retrieved July 14, 2018 from: www.psychologyboard/gov.au/standards-and-guidelines

Suttle, T. (2018). The 5 W's of clinical consultation [Blog post]. Retrieved from http://tamarasuttle.com/the-5-ws-of-clinical-consultation/

Younggren, J.N.. (2011). Psychologist duties, patient responsibilities and psychotherapy termination. Professional Psychology: Research and Practice, 42(2), 160-168.

Younggren, J.N., & Gottlieb, M.C. (2008). Termination and abandonment: History, risk, and risk management. Professional Psychology: Research and Practice, 39, 498-504.

Upcoming SCP CE webinar!

Drs. Deborah Drabick, Matt Kimble, Michael Otto, Wayne Siegel, and Doug Tynan:

Getting Your First Job in Clinical Psychology: R1, Veterans Affairs, and Liberal Arts Setting Guidelines

September 26, 2018, 6-7PM EST

Overview: Join our seasoned panelists and APA Division 12 members as they discuss how to navigate what has become an immensely competitive job market in clinical psychology. You will learn what setting is best for you including how your time is split in each these settings, and what their expectations are for promotion, as well as what goes into applying for a job in each setting, tips for putting together a compelling application and job talk, and finally, negotiation considerations and strategies. Panelists include Drs. Deborah Drabick of Temple University, Matthew Kimble of Middebury College via the Boston VA Health Care System, Michael Otto of Boston University via Massachusetts General Hospital, Wayne Siegel of the Minneapolis VA Health Care System, and Doug Tynan, of the APA Center for Psychology and Health who will share his perspectives on working in integrated health care settings. Following introductions, the panelists will cover their insights into how to go about the application process, which will be followed by a Q&A with audience members.

CE Credits Available: 1

Cost: $15 for members and $50 for Non-Members

To register, go to: http://www.div12.org/dashboard/webinar-series/

THE CLINICAL PSYCHOLOGIST
A publication of the Society of Clinical Psychology (Division 12, APA)

The Clinical Psychologist is a quarterly publication of the Society of Clinical Psychology (Div 12 of the APA). Its purpose is to communicate timely and thought provoking information in the domain of clinical psychology to the Division members. Also included is material related to particular populations of interest to clinical psychologists. Manuscripts may be either solicited or submitted. In addition, The Clinical Psychologist includes archival material and official notices from the Divisions and its Sections to the members.

Inquiries and submissions should be sent
to the Editor, Jonathan S. Comer, Ph.D. at: jocomer@fiu.edu

To subscribe, contact Tara Craighead
404.254.5062 | division12apa@gmail.com

INSTRUCTIONS FOR ADVERTISING IN THE CLINICAL PSYCHOLOGIST

Display advertising and want-ads for academic or clinical position openings will be accepted for publishing in the quarterly editions of The Clinical Psychologist.

Originating institutions will be billed by the APA Division 12 Central Office. Please send billing name and address, e-mail address, phone number, and advertisement to the editor. E-mail is preferred.

For display advertising rates and more details regarding the advertising policy, please contact the editor.

Please note that the editor and the Publication Committee of Division 12 reserve the right to refuse to publish any advertisement, as per the advertising policy for this publication.

Advances in Psychotherapy

Evidence-Based Practice

Book series developed and edited with the support of the Society of Clinical Psychology (APA Division 12)

The series provides practical evidence-based guidance on the diagnosis and treatment of the most common disorders seen in clinical practice – and does so in a uniquely reader-friendly manner. A new strand is dealing with methods and approaches rather than specific disorders. Each book is both a compact how-to reference for use by professional clinicians in their daily work, as well as an ideal educational resource for students and for practice-oriented continuing education.

39 volumes plus 4 new editions have been published to date. The first volume in a new strand dealing with methods and approaches started with the release of *Mindfulness*.

- **Practice-oriented:** The main emphasis is on information that therapists and practitioners can use in their daily practice.
- **Easy-to-read:** The most important information is summarized in tables, illustrations, or displayed boxes, and marginal notes.
- **Compact:** Each volume consists of 80-100 pages.
- **Expert authors:** We recruit genuine authorities to write for the series; many of our authors are leaders in the Society of Clinical Psychology (APA Div. 12).
- **Regular publication:** We aim to publish 4 volumes each year.
- **Reasonably priced:** The list price is under $30 per volume. Discounts are available.

About the editors

Danny Wedding, PhD, MPH

Larry E. Beutler, PhD

Kenneth E. Freedland, PhD

Linda Carter Sobell, PhD, ABPP

David A. Wolfe, PhD

Content and structure

1 Description
- 1.1 Terminology
- 1.2 Definition
- 1.3 Epidemiology
- 1.4 Course and Prognosis
- 1.5 Differential Diagnosis
- 1.6 Comorbidities
- 1.7 Diagnostic Procedures and Documentation

2 Theories and Models of the Disorder

3 Diagnosis and Treatment Indications

4 Treatment
- 4.1 Methods of Treatment
- 4.2 Mechanisms of Action
- 4.3 Efficacy and Prognosis
- 4.4 Variations and Combinations of Methods
- 4.5 Problems in Carrying out the Treatment
- 4.6 Multicultural Issues

5 Case Vignette; Further Reading; References

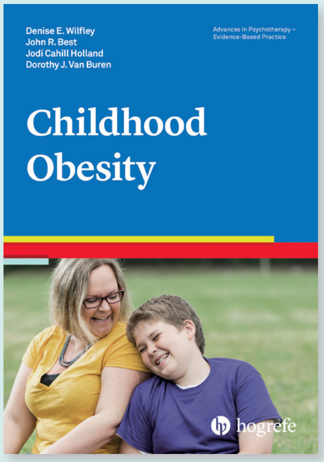
6 Appendix: Tools and Resources

Order and price information

The volumes may be purchased individually or by Series Standing Order (minimum of 4 successive volumes). The advantages of ordering by Series Standing Order: You will receive each volume automatically as soon as it is released, and only pay the special Series Standing Order price of US $24.80 – saving US $5.00 compared to the single-volume price of US $29.80.

Special prices for members of APA Division 12:
APA D12 members save US $5 on purchase of single volumes, paying only US $24.80 instead of US $29.80, and only pay US $19.80 per volume by Series Standing Order – saving US $10 per book!
In order to obtain the membership discount you must first register at www.hogrefe.com and sign up for the discount.

New titles available in the series

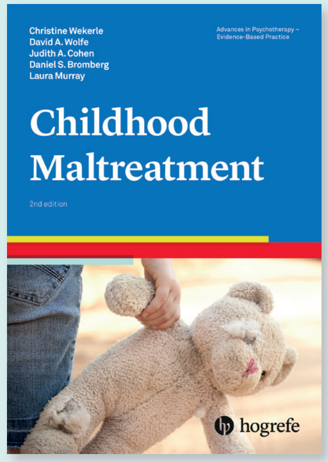


Denise E. Wilfley / John R. Best / Jodi Cahill Holland / Dorothy J. Van Buren

Childhood Obesity

Volume 39
2019, x + 76 pp.
ISBN 978-0-88937-406-5

One in every six children, and more in some ethnic groups, are obese, which can lead to serious health problems in adulthood. Successful treatment of young patients is complex, requiring time-intensive, evidence-based care delivered by a multidisciplinary team. Help is at hand with this well written, compact book by leading experts, which gives health professionals a clear overview of the current scientific knowledge on childhood obesity, from causality models and diagnosis to prevention and treatment.

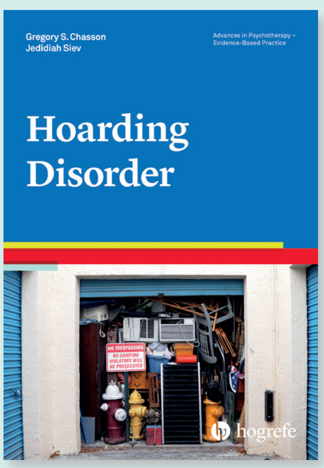


Christine Wekerle / David A. Wolfe / Judith A. Cohen / Daniel S. Bromberg / Laura Murray

Childhood Maltreatment

Volume 4
2nd ed, 2019. viii + 100 pp.
ISBN 978-0-88937-418-8

The new edition of this popular, evidence-based guide compiles and reviews all the latest knowledge on assessment, diagnosis, and treatment of childhood maltreatment – including neglect and physical, sexual, psychological, or emotional abuse. Readers are led through this complex problem with clear descriptions of legal requirements for recognizing, reporting, and disclosing maltreatment as well as the best assessment and treatment methods. The focus is on the current gold standard approach – trauma-focused CBT.



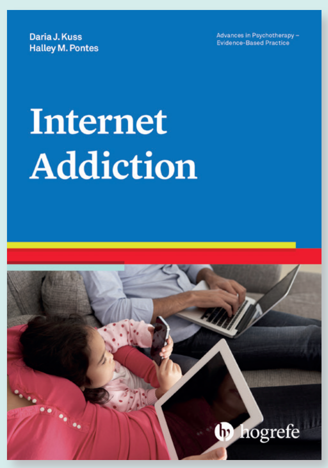
Gregory S. Chasson / Jedidiah Siev

Hoarding Disorder

Volume 40
2019, approx. viii + 88 pp.
ISBN 978-0-88937-407-2

Due September 2018

Hoarding disorder is a new subtype of obsessive compulsive disorder in the DSM-5 that presents particular challenges in therapeutic work, including the poor treatment adoption and lack of awareness of those affected. This evidence-based guide written by leading experts presents the busy practitioner with the latest knowledge on assessment and treatment of hoarding disorder. The reader gains a thorough grounding in the treatment of choice for hoarding – a specific form of CBT interweaved with psychoeducational, motivational, and harm reduction approaches to ensure successful treatment. Includes information for special client groups: the elderly and hoarding with animals. Printable tools help practitioners carry out therapy.



Daria J. Kuss / Halley M. Pontes

Internet Addiction

Volume 41
2019, approx. viii + 88 pp.
ISBN 978-0-88937-501-7

Due October 2018

Internet use has become an integral part of our daily lives, but at what point does Internet use become problematic? What are the different kinds of Internet addiction? And how can professionals best help clients? Internet addiction refers to a range of behavioral problems, including social media addiction and Internet gaming disorder. This compact, evidence-based guide written by leading experts from the field helps disentangle the debates and controversies around Internet addiction and outlines the current assessment and treatment methods. The book presents a 12–15 session treatment plan for Internet and gaming addiction using the method and setting with the best evidence: group CBT. Printable tools in the appendix help clinicians implement therapy.

Volumes available for CE credits

Children & Adolescents

- **Childhood Maltreatment, 2nd ed.** by Christine Wekerle / David A. Wolfe / Judith A. Cohen / Daniel S. Bromberg / Laura Murray (2019)
- **Childhood Obesity** by Denise E. Wilfley / John R. Best / Jodi Cahill Holland / Dorothy J. Van Buren (2019)
- **ADHD in Children and Adolescents** by Brian P. Daly / Aimee K. Hildenbrand / Ronald T. Brown (2016)

Anxiety and Related Disorders

- **Hoarding Disorder** by Gregory S. Chasson / Jedidiah Siev (2019)*
- **Obsessive-Compulsive Disorder in Adults** by Jonathan S. Abramowitz / Ryan J. Jacoby (2014)
- **Generalized Anxiety Disorder** by Craig D. Marker / Alison Aylward (2011)
- **Social Anxiety Disorder** by Martin M. Antony / Karen Rowa (2008)

Behavioral Medicine and Related Areas

- **Alzheimer's Disease and Dementia** by Benjamin T. Mast / Brian P. Yochim (2018)
- **Multiple Sclerosis** by Pearl B. Werfel / Ron E. Franco Durán / Linda J. Trettin (2016)
- **Headache** by Todd A. Smitherman / Donald B. Penzien / Jeanetta C. Rains / Robert A. Nicholson / Timothy T. Houle (2014)
- **Chronic Pain** by Beverly J. Field / Robert A. Swarm (2008)
- **Treating Victims of Mass Disaster and Terrorism** by Jennifer Housley / Larry E. Beutler (2006)

Methods and Approaches

- **Mindfulness** by Katie Witkiewitz / Corey R. Roos / Dana Dharmakaya Colgan / Sarah Bowen (2017)

Addictions and Related Disorders

- **Internet Addiction** by Daria J. Kuss / Halley M. Pontes (2019)*
- **Substance Use Problems, 2nd ed.** by Mitch Earleywine (2016)
- **Women and Drinking: Preventing Alcohol-Exposed Pregnancies** by Mary M. Velasquez / Karen Ingersoll / Mark B. Sobell / Linda Carter Sobell (2015)
- **Binge Drinking and Alcohol Misuse Among College Students Young Adults** by Rachel P. Winograd / Kenneth J. Sher (2015)
- **Nicotine and Tobacco Dependence** by Alan L. Peterson / Mark W. Vander Weg / Carlos R. Jaén (2011)
- **Alcohol Use Disorders** by Stephen A. Maisto / Gerard J. Connors / Ronda L. Dearing (2007)
- **Problem and Pathological Gambling** by James P. Whelan / Timothy A. Steenbergh / Andrew W. Meyers (2007)

Sexual Disorders

- **Sexual Dysfunction in Women** by Marta Meana (2012)
- **Sexual Dysfunction in Men** by David Rowland (2012)
- **Sexual Violence** by William R. Holcomb (2010)

Other Serious Mental Illnesses

- **The Schizophrenia Spectrum, 2nd ed.** by William D. Spaulding / Steven M. Silverstein / Anthony A. Menditto (2017)
- **Bipolar Disorder, 2nd ed.** by Robert P. Reiser / Larry W. Thompson / Sheri L. Johnson / Trisha Suppes (2017)
- **ADHD in Adults** by Brian P. Daly / Elizabeth Nicholls / Ronald T. Brown (2016)
- **Depression** by Lynn P. Rehm (2010)
- **Suicidal Behavior** by Richard McKeon (2009)

* in preparation

Also available in the series

- **Autism Spectrum Disorder** by Lisa Joseph / Latha V. Soorya / Audrey Thurm (2014)
- **Language Disorders in Children and Adolescents** by Joseph H. Beitchman / E. B. Brownlie (2013)
- **Phobic and Anxiety Disorders in Children and Adolescents** by Aime E. Grills-Taquechel / Thomas H. Ollendick (2012)
- **Growing Up with Domestic Violence** by Peter Jaffe / David A. Wolfe / Marcie Campbell (2011)
- **Nonsuicidal Self-Injury** by E. David Klonsky / Jennifer J. Muehlenkamp / Stephen P. Lewis / Barrent Walsh (2011)
- **Public Health Tools for Practicing Psychologists** by Jalie A. Tucker / Diane M. Grimley (2011)
- **Hypochondriasis and Health Anxiety** by Jonathan S. Abramowitz / Autumn E. Braddock (2011)
- **Elimination Disorders in Children and Adolescents** by Edward R. Christophersen / Patrick C. Friman (2010)
- **Eating Disorders** by Stephen W. Touyz / Janet Polivy / Phillippa Hay (2008)
- **Chronic Illness in Children and Adolescents** by Ronald T. Brown / Brian P. Daly / Annette U. Rickel (2007)
- **Heart Disease** by Judith A. Skala / Kenneth E. Freedland / Robert M. Carney (2005)

Forthcoming volumes

- **Insomnia**
- **Dating Violence**
- **Body Dismorphic Disorder**
- **Bullying and Peer Victimization**
- **Posttraumatic Stress Disorder**
- **Domestic Violence**
- **Panic Disorder and Agoraphobia**
- **Persistent Depressive Disorder**