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Personalized Models of Psychopathology

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Abstract

The personalized approach to psychopathology conceptualizes mental disorder as a complex system of contextualized dynamic processes that is nontrivially specific to each individual, and it seeks to develop formal idiographic statistical models to represent these individual processes. Although the personalized approach draws on long-standing influences in clinical psychology, there has been an explosion of research in recent years following the development of intensive longitudinal data capture and statistical techniques that facilitate modeling of the dynamic processes of each individual's pathology. Advances are also making idiographic analyses scalable and generalizable. We review emerging research using the personalized approach in descriptive psychopathology, precision assessment, and treatment selection and tailoring, and we identify future challenges and areas in need of additional research. The personalized approach to psychopathology holds promise to resolve thorny diagnostic issues, generate novel insights, and improve the timing and efficacy of interventions.

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A TRANSDISCIPLINARY SHIFT

Arguably, no human affliction is more personal than psychopathology. It impacts the core of who we are: how we perceive, think, feel, behave, and relate. Furthermore, due to the rich individual differences in human personality and functioning, there may well be as many manifestations of psychopathology as there are individuals to experience them. To the extent that this is true, models of psychopathology should be personalized to each individual. There is an emerging push toward personalizing diagnosis and intervention across fields as diverse as medicine (Collins & Varmus 2015, Jameson & Longo 2015), prevention science (Ridenour 2019), education (Reber et al. 2018), and psychology (Molenaar 2004). The shared impetus for these calls is the growing recognition that there is staggering heterogeneity in how each individual functions, and one-size-fits-all, or even one-size-fits-most, approaches to diagnosis and intervention are perilously inadequate. The rising calls for personalization are motivated by the typically disappointing, yet highly varied, responses to interventions among the individuals who share some putatively homogeneous diagnosis (e.g., breast cancer, migraine, irritable bowel syndrome, depression). The assumption is that greater precision in characterizing individual differences in pathologies will translate into greater scientific yield, more accurate diagnoses, better match of intervention to individuals, and ultimately better treatment response. Clinical psychology and psychiatry are currently at the forefront of the personalization movement through efforts to research, diagnose, and treat mental illness using individualized models (Fisher 2015, Wichers 2014, Wright et al. 2016).

Polythetic criteria: psychiatric diagnoses generally require that some subset of the total criteria, but not all criteria, be present in order to assign a diagnosis

WHAT ARE PERSONALIZED MODELS OF PSYCHOPATHOLOGY?

At the most basic level, personalized models move beyond current systems of classifying and diagnosing mental illness that presume individuals with the same diagnosis share the same pathological processes. That psychiatric diagnoses poorly capture the complexity of mental illness is so well recognized as to be engineered into their design. Features such as polythetic criteria sets and subtype specifiers attempt to accommodate the observed clinical heterogeneity—poorly, as it

turns out. Intracategory heterogeneity and intercategory overlap are so large that many prominent scholars have declared contemporary systems of diagnosis to be fundamentally broken (Hyman 2010). Paradoxically, the available diagnostic systems are simultaneously too general and too specific. In response, researchers have proposed more scientifically and clinically robust diagnostic systems, including the Hierarchical Taxonomy of Psychopathology (Kotov et al. 2017) and the National Institute of Mental Health's Research Domain Criteria (Insel 2014), which use different approaches to identify fundamental domains of psychopathology that could be used to provide a more nuanced and accurate picture of an individual's mental disorder. Rather than providing coarse labels of putative syndromes, these approaches offer profiles of functioning that could be used for finer-tuned diagnosis.

However, personalized models of psychopathology go beyond these efforts. That is because large omnibus models of psychopathology built on individual differences still require us to fit the person to the model, not tailor the model to the person. They establish the major domains that constitute the structure of psychopathology, akin to the morphology or anatomy of mental disorder. They do not establish the functional processes underlying and linking different domains, akin to the physiology of mental disorder. These nomothetic models tell us how individuals differ from one another, but not how any one person differs from themself at distinct points in time, which is the basis of a functional understanding of psychopathology. In large part, this is because of a mismatch between the level of data upon which the models are based and the level of data upon which we would like to make scientific and clinical inferences. Empirically supported psychopathology models are generally grounded in between-person data, whereas the majority of clinical theories, and the points of intervention targeted in clinical practice, emphasize within-person processes and mechanisms (Voelkle et al. 2014). The inferences drawn at one level need not, and in many cases are unlikely to, transfer to the other (Molenaar 2004). Often discussed in terms of (lack of) ergodicity or ergodic theorems, the key point is that there is no mathematical requirement for the within-individual processes of an individual to follow the same form as the between-person structure. Moreover, individuals differ from one another in their within-person processes (Brose et al. 2015, Fisher & Boswell 2016, Wright et al. 2016). For instance, at the between-person level, individuals who are more anxious are, on average, also more hostile than other individuals (Costa & McCrae 2008), but this does not necessarily imply that, at the within-person level, when individuals are more anxious they are also more hostile. Our bet is that readers can think of individuals who when anxious are indeed more hostile, and other individuals for whom the opposite is true, such that their anxiety is coupled with obsequiousness and reassurance seeking. These sorts of within-person patterns of behavior are presumed to have critical clinical import (Wright 2011) and are the primary focus of many ubiquitous frontline treatments for psychopathology (Beck et al. 1979, Clarkin et al. 2006, Hayes et al. 2012, Linehan 1993).

In clinical practice, psychopathology has traditionally been conceptualized as an idiographic (i.e., person-specific) phenomenon. Although clinical theories are generally derived from nomothetic principles, clinicians often tailor these general principles to the specific presentation of the patient in front of them (Hamilton et al. 2008, Kuyken et al. 2011, Norcross & Wampold 2011). Clinicians rarely if ever see the prototypical client described in their treatment guides and manuals and must adapt their therapy to the unique instantiation of psychopathology manifesting in the consulting room. In fact, some of the nomothetic principles taken for granted by the theoretical orientation may or may not apply to some individuals, which may explain the relatively tepid success rate of frontline psychotherapies. For example, cognitive–behavioral theory holds that negative thoughts will elicit negative affect; thus, negative thoughts should be a target of treatment. However, the extent to which cognitions are linked to affect at all may vary between individuals and even within individuals across time and situations. Those with a strong link may benefit from

Nomothetic: refers to the scientific pursuit of generalizable laws or principles; in psychology, it refers to the search for principles that are true of all individuals in a group or population

Ergodicity: the property whereby each individual component (i.e., person) of a dynamic system is equally representative of the whole group (i.e., population)

Idiographic: refers to the scientific study of a specific instance, such as one country or language; in psychology, it generally refers to the study of each individual

Dynamic: refers, in this context, to a process or system that is characterized by change, fluctuation, or movement (i.e., not static)

an orthodox regimen of cognitive–behavioral therapy, while those with a weak connection may not—and the experienced clinician will likely naturally adapt their approach to the connection in symptom response reported by the patient. Thus, both patient and clinician are in a position to gain from personalized models of psychopathology that do not assume homogeneity between individuals with the same diagnosis or even the same cluster of prominent symptoms. Note that the personalized modeling approach does not argue that clinicians and researchers discard theoretical principles; indeed, they are useful insofar as they provide an organizational scaffolding to understand the processes at play in patients, as well as a common language for communicating with other clinicians and researchers. Furthermore, to the extent that different patients' disorders are governed by distinct processes, it is likely that no one theoretical model can adequately explain each individual's pathology. A pillar of the personalized approach is that the traditional assumption of homogeneity of dynamic processes within individuals—even those with the same diagnosis—is suboptimal and shifts the question away from the global (which theoretical model is best?) to the specific (which theoretical model is best for understanding this person's behavior?).

However, for much of the past century, there has been a dearth of research into the nature and treatment of psychopathology on the basis of idiographic or person-specific premises. Although most psychopathology and psychotherapy research has relied on nomothetic designs using group averages to derive principles about the wider population, it is worth noting a few traditions that have continued to rely on idiographic research techniques and whose literatures can be consulted so as to not reinvent the wheel as personalized models become more prominent. One of the oldest traditions is applied behavior analysis, which traces its methodology back to B.F. Skinner and his principles of behavior (Skinner 1966). Functional analysis in applied behavior analysis is an example of a tool of idiographic assessment: The therapist attempts to establish the antecedent conditions for eliciting a target behavior within a specific patient (Hofmann & Hayes 2019b). A related tradition that has similarly focused on the person but has adapted to the explosion of techniques to address maladaptive cognitions is cognitive–behavioral case formulation (Mumma & Fluck 2016, Mumma et al. 2018). In addition, the entire methodology of single-case experimental designs (sometimes referred to as $n = 1$ designs; Barlow et al. 2009, Bentley et al. 2018, Ganz & Ayres 2018) has been built to help facilitate more reliable and valid idiographic assessment.

Although these traditions rely on idiographic assessment techniques, each of them, perhaps with the exception of cognitive–behavioral case formulation, typically focuses on intensively studying one or two mechanisms by examining the relationships between only a couple to a few variables. The emerging approach to personalized models of psychopathology often seeks to go beyond this circumscribed scope to capture the whole psychopathology system, in context, with as much relevant information as can feasibly be gathered. It is generally insufficient to understand only the functional relationships between a given antecedent and symptom, for example; rather, the aim is to capture multiple domains implicated in psychopathology to understand psychopathology as an integrated and multisystemic process (Beltz et al. 2016, Boswell et al. 2014, Hayes et al. 2019, Hopwood et al. 2016).

The personalized modeling approach toward psychopathology conceptualizes psychopathology as a complex system of contextualized dynamic processes that is nontrivially specific to each individual, which can be approximated with a formal idiographic statistical model. As such, it recognizes that:

1. Psychopathology is highly heterogeneous in its manifestation, and official diagnostic nosologies fail to provide sufficient information for mechanistic clinical research or effective clinical intervention.

2. Models of psychopathology based on between-person structure, although highly important, do not directly identify mechanistic processes at the level necessary for intervention.
3. Formal within-person process–based models should be developed for each patient in order to provide a tailor-made understanding of their particular clinical presentation.

Others have used the terms precision diagnosis (Roche et al. 2014; Roche & Pincus 2016; van Os et al. 2013a,b; Wichers 2014), person-specific (Molenaar 2004, Molenaar & Campbell 2009, Wright et al. 2019), and idiographic (Beltz et al. 2016, Fisher et al. 2017, Haynes et al. 2009) in the same way the term personalized is used here.

To illustrate the dynamic and individualized nature of psychopathology that motivates the personalized movement, we present data from four outpatients who completed daily diaries for approximately 100 days each (Wright & Simms 2016), including daily ratings of scales related to five broad spectra of psychopathology (negative affectivity, detachment, impulsivity, hostility, psychoticism) and stress. **Figure 1** depicts each case's data using kernel density plots, which illustrate average values and dispersion; time-series plots, which demonstrate the temporal sequencing of daily experiences; and correlational heat maps, which convey the interplay among the various domains and their carryover from day to day. What should be readily apparent is that each of these cases differs from the others not only in the level of pathology (density plots) but also in the range of symptom experiences (density plots), the temporal fluctuation of symptoms across days (time series), and how the domains associate with one another and with stress (correlations). These plots convey that some individuals are quite consistent in their pathology over time (Participants A and C) whereas others vary widely (Participants B and D). For some, the associations among domains are loose (correlations for Participants A and D), whereas for others, these domains are tightly correlated (correlations for Participants B and C). The takeaway is that each of these patients' data comprise contextualized dynamic processes that are unique to each individual.

Using these sorts of multivariate data sampled intensively and longitudinally, promising research has already begun in more comprehensive, personalized assessment and diagnosis (David et al. 2018, Haynes et al. 2009, Hofmann & Hayes 2019a, Roche et al. 2014). The subsequent sections of this review describe in more detail areas of success in person-specific modeling as well as areas for future research. However, as we discuss further below, individualization does not preclude identifying and exploiting generalizable features and common themes, although bridging the traditional nomothetic–idiographic divide remains a formidable challenge in this area. By starting with assumptions of heterogeneity, we can search for points of convergence across individuals, but starting with assumptions of homogeneity makes it very difficult to then accommodate this individuality.

WHY PERSONALIZE PSYCHOPATHOLOGY NOW?

As noted in the preceding section, there has been long-standing interest in idiographic assessment and modeling in clinical psychology (Shapiro 1961) and allied domains like personality (Allport 1937). So why is the push toward personalization emerging with such enthusiasm now? In essence, it reflects the confluence of three streams of relevant conceptual and technological developments. These correspond to the three major components of scientific inquiry—theory, data capture, and statistical analysis—which must all be synchronized to achieve sensible inferences. First, the neo-Kraepelinian movement was a major transformative force in psychiatry and clinical psychology in the 1970s that oriented the mental health fields toward validating mental disorders as discrete disorders or syndromes (Robins & Guze 1970), culminating in the modern *Diagnostic and Statistical Manual of Mental Disorders* (APA 1980). As we describe above, promise and interest in this approach

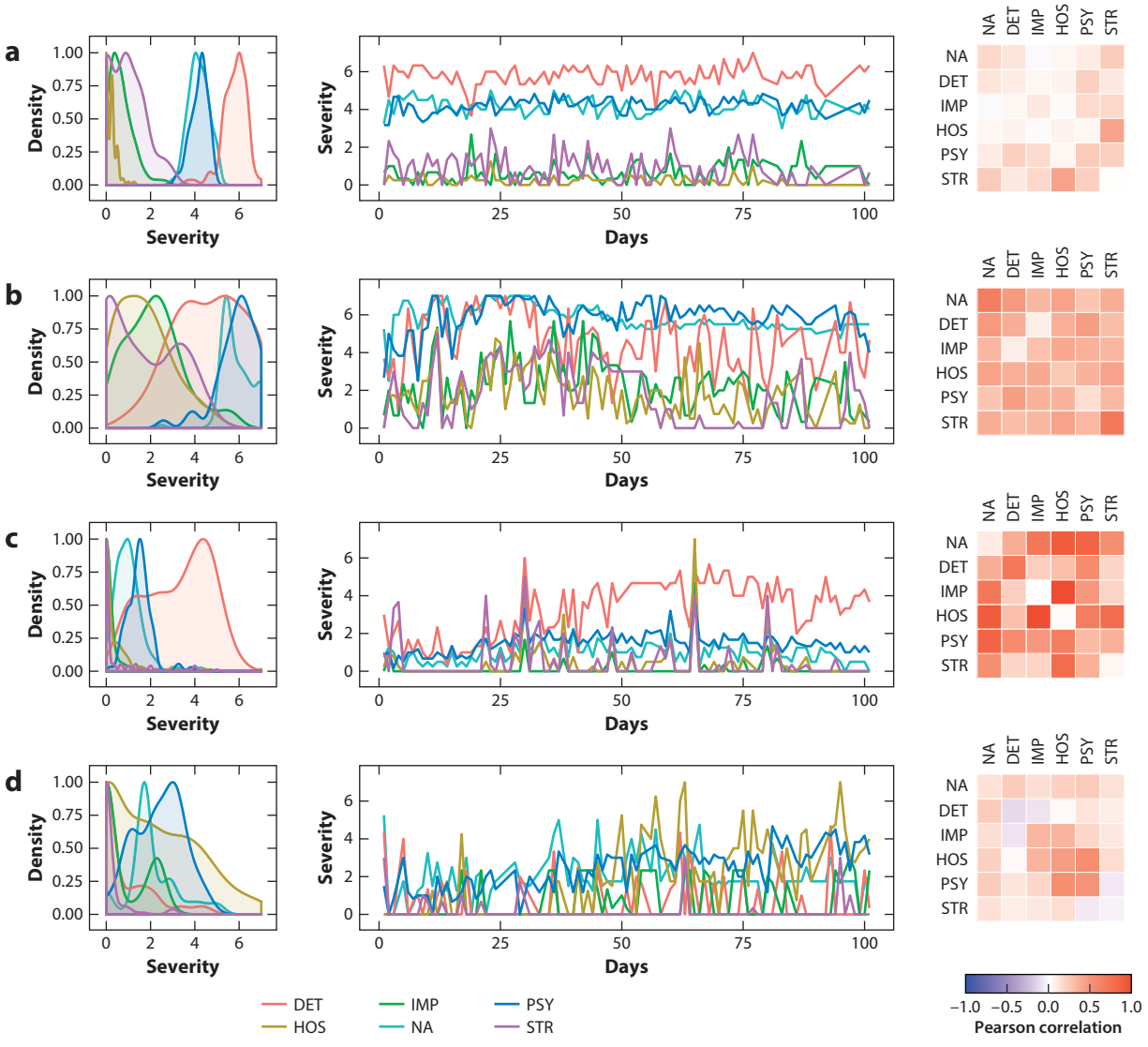

Figure 1

(*left*) Kernel density plots, (*middle*) time-series plots, and (*right*) correlation heat maps of daily assessed negative affectivity (NA), detachment (DET), impulsivity (IMP), hostility (HOS), psychoticism (PSY), and stress (STR) for four psychiatric outpatients (Participants A–D, shown in panels *a–d*, respectively) who completed approximately 100 days of assessments. The heat maps convey the interplay among the various domains (off-diagonals) and their carryover from day to day (diagonal reflects autocorrelation).

have given way to pessimism and disenchantment as researchers and clinicians have started to come to terms with its limitations.

Second, the rise of intensive longitudinal data sampling has provided the necessary multivariate dynamic data sampled enough times to develop a model for each person. Relevant techniques include ambulatory assessment, which allows for the sampling of many variables in an intensive and longitudinal fashion in an individual's own environment, thereby maximizing ecological validity (Trull & Ebner-Priemer 2013). This sampling may be obtrusive, via questionnaires and surveys,

or unobtrusive, via passive sensing (Mohr et al. 2017, Shiffman et al. 2008). The rise of ambulatory assessment in clinical science (Hamaker & Wichers 2017) has been propelled by the proliferation of smartphones (Pew Res. Cent. 2019). However, although ambulatory assessment has served as a natural catalyst, personalized models are not limited to naturalistic sampling, and any intensive longitudinal data [e.g., from functional magnetic resonance imaging (fMRI)] may provide appropriate information. For instance, Price et al. (2017) arrived at personalized models of brain connectivity among individuals with and without diagnoses of depression.

Third, there has been a growing armamentarium of statistical models developed precisely for the analysis of multivariate intensively sampled data and the computational architecture needed to support their widespread and easy implementation. Some of these are the same generic developments fueling advancement across the sciences, like inexpensive and ubiquitous powerful computing. Others are more esoteric and specific to this domain, such as the development of algorithms and software to analyze person-specific longitudinal data.

Together, the shift in thinking, ability to collect appropriate data, and easier implementation of sophisticated statistical models are sufficient to fuel the personalized modeling of psychopathology. Although listed as if they are separate, each of these components interdigitates and mutually influences the development of the others. Sometimes technological advances compel novel theoretical questions (e.g., If we can now sample processes in real time, what is the timescale on which these processes unfold?); sometimes conceptual questions motivate the development of new statistical models (e.g., If we want to continuously track patients through therapy, can the model change with them?). Continued interest in personalizing psychopathology models will sustain rapid advancement in each of these areas.

WHAT TYPES OF DATA ARE NECESSARY, AND WHICH VARIABLES SHOULD BE USED IN THE MODEL?

The ability to understand individualized processes with reliability and validity is necessarily built upon a foundation of strong assessment practices (Wright & Zimmermann 2019). Nearly all idiographic research is united in its reliance on longitudinal data, that is, data that are collected over time and across situations. Two questions arise immediately when discussing collection of longitudinal data: For how long should data be collected, and at what frequency? Neither question has a definitive answer and will almost invariably need to be balanced by the needs of the researcher and the burden on the person being assessed. For example, Roche et al. (2014) assessed their participant over a period of 21 days to understand the individual's interpersonal dynamics, while Bos et al.'s (2012) assessment of the effect of weather on internalizing symptoms lasted nearly 8 months. Another technique that allows for longer-term assessment with lesser participant burden is so-called burst assessments, in which the individual is intensively sampled for several days at a time with weeks or months between assessment intervals (Yang et al. 2018), balancing the need for measuring individuals at a granular level over an extended period with not being overly burdensome. Separately modeling discrete bursts of assessment might also facilitate pre–post intervention change.

The second question, regarding data collection frequency, follows naturally from the length of the assessment period. Individuals may be more amenable to being intensively sampled (i.e., multiple times per day) for days to weeks (Fisher et al. 2017, 2019; van der Krieke et al. 2016; Wright et al. 2016), but this may need to be scaled back to once a day (i.e., daily diaries; Rosmalen et al. 2012, Wright & Simms 2016) over months or longer. Related to participant burden is the question of what frequency is needed to accurately capture the constructs of interest. This will obviously vary by what is being assessed. For example, individuals may go extended periods without

Autocorrelation: degree to which a variable is associated with itself from one time point to the next; a measure of stability of states

engaging in self-harm, so multiple assessments per day may be overly burdensome. However, for most people, social interactions occur frequently throughout a typical day, so to fully capture an individual's social behavior more frequent assessments may be necessary. Of course, the above is predicated on using time-based assessments in which measures are "pushed" to the participant. Alternative strategies, such as event-contingent recording, where individuals manually initiate a report after each occurrence, are also available. Although there are valid concerns that both event and prompted assessments may fail to capture the phenomenon of interest completely, preliminary research on social behavior and affect suggests that these methods do not result in differences in data quality (Himmelstein et al. 2019).

Assessment methods for ambulatory research are becoming increasingly sophisticated; however, self-report measures remain the primary data source of choice for most studies. A challenge for researchers interested in personalized models is the dearth of measures designed specifically to assess constructs longitudinally (Hamaker et al. 2017, Wright & Zimmermann 2019). Indeed, many studies simply adapt items that were developed for single-occasion, cross-sectional research without proper psychometric evaluation of their performance in this new longitudinal context. That said, researchers are increasingly developing and validating their items for ambulatory assessment (Edershile et al. 2019, Lee et al. 2017, Tomko et al. 2014). A critical issue specific to this context is whether the questions should be tailored to the individual or be standardized across individuals (Elliott et al. 2016, Haynes et al. 2009, Shapiro 1961, Wright & Zimmermann 2019). To fully personalize an assessment protocol, one can create an idiographic battery, either by selecting a relevant subset of standard stimuli (e.g., only include affective adjectives related to anger and shame if the patient rarely experiences anxiety) or by engineering idiosyncratic stimuli that capture an individual's unique experience (e.g., "My husband used *that* tone with me"; "I had difficulties correctly naming my grandchildren"). As a rule, personalized assessment is likely to engage more with the person being assessed than in traditional studies. Specifically, this is achieved by selecting or crafting assessment variables in consultation with patients (Bos et al. 2012; Jones & Hurrell 2019; Mumma 2004; Mumma & Mooney 2007a,b; Rodgers et al. 2018; Shapiro 1961), rather than simply using a standardized protocol, and coupling it with automated generation of individualized feedback (Blaauw et al. 2017).

However, idiographic batteries or items raise challenging questions for the personalized assessment paradigm. On the one hand, they offer the highest degree of personalization and therefore may increase sensitivity, validity, and predictive power for a given individual. On the other hand, they make any comparison or integration with results of others or generalization of principles more challenging. As Wright & Zimmermann (2019) argue, even if the goal is developing a personalized model, there may be utility in traditional nomothetic comparisons, in part because decontextualized statistical coefficients are difficult to interpret without some form of normative comparison. Knowing that a patient's autocorrelation for negative affect is 0.3 offers little in the way of whether it is problematically high, low, or normative. Being able to generalize and draw inferences about normativity favors a moderate approach of personalizing a model but retaining a standard stimulus set. At the same time, some investigators have demonstrated that one can vary the precise stimulus but use it in place of a generic category that does generalize (e.g., problem behavior; Rodgers et al. 2018).

Of course, self-report is not the only form of assessment available to those interested in personalized assessment. Several studies have included physiological measurements such as cortisol (Booij et al. 2015; Toonen et al. 2016a,b), heart rate (Hartogs et al. 2017, Hoenders et al. 2012), and melatonin (Bouwmans et al. 2015). Another area of growth is in passive sensing—especially the use of sensors already available on individuals' smartphones to collect information such as location, presence of others, and activity level (Bentley et al. 2018, Blaauw et al. 2016). This kind of

information is being used to predict traditionally subjective psychological phenomena such as personality (Wang et al. 2018), oncological symptom severity (Low et al. 2017), critical behaviors such as alcohol use as they are occurring (Bae et al. 2018), or medical readmission (Doryab et al. 2019).

The future of personalized ambulatory assessment appears to be firmly multimethod: blends of self-reported, physiological, and/or passive sensing data (Booij et al. 2015, 2016; Bouwmans et al. 2018; Lewis & Ridenour 2019; Low et al. 2017; Mohr et al. 2017; Stavrakakis et al. 2015). Combining the reports of subjective psychological states with more objective physiological indicators may be useful for understanding and treating disorders with somatic features (Hartogs et al. 2017). Similarly, insights into an individual's psychological states in different settings, as assessed by more objective indicators such as number of individuals present or time and proximity to bars, may give clinicians useful information that even the most well-intentioned patient may be unable to relay accurately due to burden, or due to imperfections or biases of recall (Wang et al. 2018).

HOW DOES ONE BUILD PERSONALIZED MODELS OF PSYCHOPATHOLOGY?

Currently, the most common model used for studying within-person processes in clinical psychology is the multilevel model, but it must be distinguished from truly person-specific models (Piccirillo & Rodebaugh 2019). At first glance, multilevel models may seem idiographic, in the sense that they model within-person variations and accommodate individual differences in values with random effects (Conner et al. 2009). However, this is deceptive, because the actual model does not estimate person-specific effects but rather is based on the estimation of an average fixed effect and a variance for that effect. Under certain circumstances this estimation may offer a reasonable approximation of the distribution of individual effects, but in many modeling scenarios (e.g., widely varying or highly skewed patterns of individual effects) the parameter estimates can be biased. Instead, personalized models emphasize an idiographic approach to modeling that leaves each individual's parameter values unconstrained by those of other participants in the sample.

Truly idiographic models come in several forms, each with its own goals and underlying model assumptions. Nearly all modern idiographic analyses use intensive longitudinal (i.e., time-series) data from a single individual. At a rudimentary level, descriptive statistics commonly estimated in samples of individuals, such as the mean, variance, and skewness, can be estimated from the sample of an individual's states to begin to make inferences about the person (e.g., **Figure 1**, *left*). These begin the process of considering the form and function of an individual's behavior. Calculating dynamic correlations among variables (**Figure 1**, *right*) or among variables with time (i.e., a trend) begins to reveal the patterning or structure of an individual's functioning. These correlations are correctly understood as dynamic, because they reflect the covariation of variables as they move together or independently through time or with time. For example, Boswell & Schwartzman (2018) provided a case study of a personalized treatment which used routine monitoring of client symptoms to suggest when the use of particular interventions was warranted and the influence of those interventions on the client's symptoms (i.e., the correlation between intervention and symptom expression). Above, we have indicated that personalized models of psychopathology often extend beyond univariate analyses of a single outcome and seek to approximate a reasonably comprehensive structure of the complex dynamic system of an individual's pathology (Wichers et al. 2018). Although we believe that this is a defining aspiration of this approach, we do not wish to suggest that there are minima to the number of variables or parameters a model must include. The complexity of psychopathology generally places a comprehensive assessment of all relevant variables beyond what is feasible in most scenarios. Thus, difficult choices about what to include

must be made and are best informed by some guiding theory, such as a case formulation (Mumma & Mooney 2007a,b). Furthermore, the number of different forms of time-series analyses available and the lack of consensus on which method should be used and when (Bastiaansen et al. 2019, Smith 2012) preclude an all-inclusive treatment here, so in this section we cover some common modeling techniques and point to directions of development.

One of the most common idiographic analytic techniques is vector autoregression (VAR) (Brandt & Williams 2006). The basic VAR model (and other models we discuss below) has two components: autoregressive and cross-lagged effects. The former estimates the extent to which a variable predicts itself at the next time point. The latter estimates the effect of variable A at time 1 on variable B at time 2. The autoregressive component can be interpreted as the tendency for a state to persist over time. Accordingly, positive values reflect a tendency to persist or to get stuck in a state, whereas negative values suggest a regulatory or compensatory process operant between observations. Snippe et al. (2015) measured temporal associations among depressive symptoms, mindfulness, and repetitive thinking in six women, using separate VAR models for each participant. The extent to which a given participant's depression on one day tended to predict depression on the next day represents the autoregressive value in the VAR model: Individuals who tend to experience periods where they remain in relatively stable states—low or high—would have high autoregressive values. The cross-lagged component helps explain the temporal relationships between multiple variables of interest and may provide some insight into the temporal effects of variables. In Snippe and colleagues' study, some but not all participants showed that a change in daily mindfulness predicted a change in next-day depressive symptoms. VAR models have been used extensively for idiographically studying topics including relationships between physical activity and depression (Booij et al. 2016, Rosmalen et al. 2012, van der Krieke et al. 2015) and between atopic diseases and attention-deficit/hyperactivity disorder symptoms (van der Schans et al. 2020). They are becoming increasingly popular as methods of passive sensing become more sophisticated (Blaauw et al. 2016, Bos et al. 2018).

VAR modeling is a classic example of a technique that simultaneously estimates many associations within a multivariate time series of observed variables. However, the standard VAR is relatively restricted in many ways—discussion of which is beyond the scope of this review—and consequently extensions of this method are commonly employed in the literature on personalized modeling of psychopathology. Examples of such models include unified structural equation modeling (uSEM) (Kim et al. 2007), which marries structural equation modeling and VAR; graphical VAR (gVAR) (Epskamp et al. 2018), which combines VAR and Gaussian graphical models; and dynamic structural equation modeling (DSEM) (Asaparouhov et al. 2018), which integrates structural equation modeling, multilevel modeling, and time-series analysis. Details of the differences between these methods are beyond the scope of this article; however, these methods all increase the modeling flexibility (e.g., contemporaneous associations, structured residuals) and potential informational yield of a multivariate time series. Using some variation of these VAR extensions has become the most popular approach in the recent personalized psychopathology literature. For instance, Wright and colleagues (Beltz et al. 2016; Dotterer et al. 2019; Lane et al. 2019; Woods et al. 2020; Wright et al. 2015, 2019) have used uSEM-based models to examine heterogeneity in the structure of personalized models of personality pathology, and Fisher et al. (2017, 2019) have done similar research in internalizing disorders.

To illustrate the types of results generated from this general class of models, **Figure 2** presents graphs of uSEM-based models estimated from the data of the four participants shown in **Figure 1**. The four plots provide a sense of the high degree of heterogeneity in within-person dynamic patterns across individuals, although there are some notable similarities. Among these personality-disordered individuals, daily stress is associated with hostility, and among Participants A, B, and

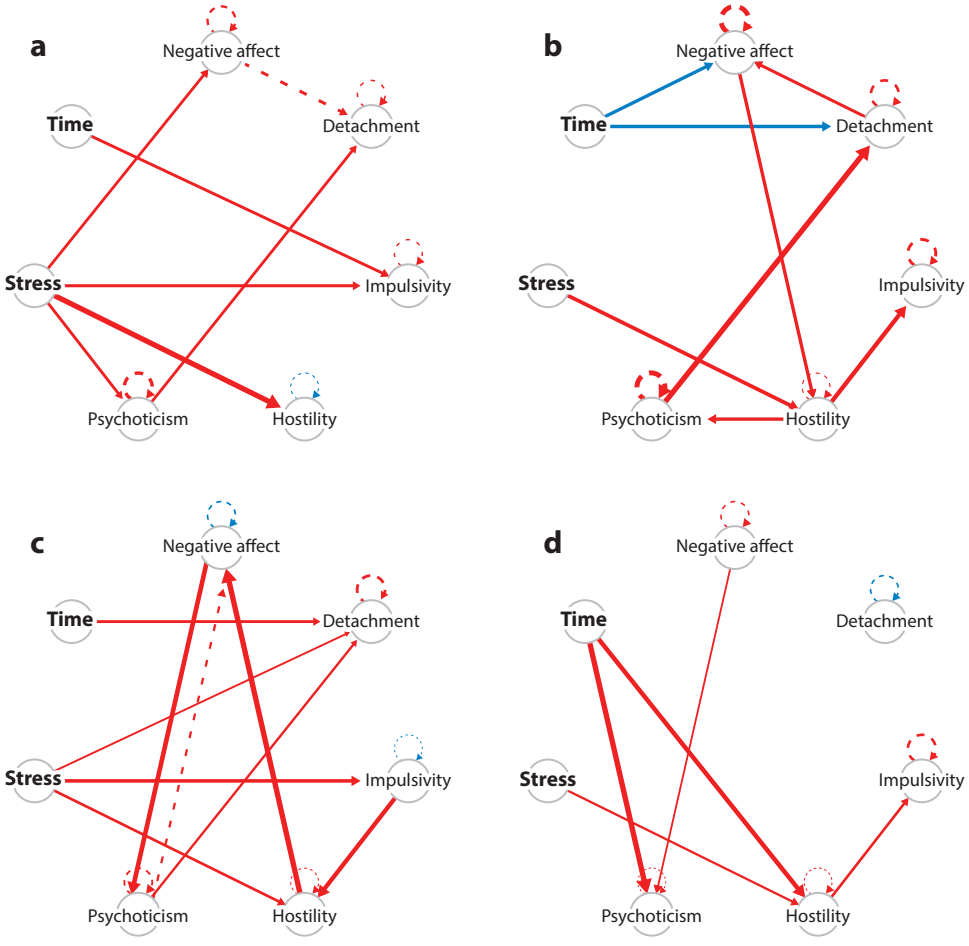

Figure 2

Unified structural equation model plots corresponding to the data from Participants A–D (panels *a–d*, respectively) in **Figure 1**. Circles represent variables, arrows represent regression paths (*red* for positive effects, *blue* for negative effects), solid arrows are contemporaneous (same day), and dashed arrows are lagged (from one day to the next). Arrow width represents strength of associations. Time (day in study) and stress are treated as exogenous; therefore, they only predict other variables and cannot be predicted by other variables. All other variables can be both predictors and outcomes.

C, psychoticism is associated with detachment (although the strength of this effect differs). In a clinical setting, these types of graphs might be used to select optimal targets for intervention (e.g., Participant A's graph suggests that stress predicts increases in almost all domains of pathology). They also have the potential to identify positive feedback loops that might serve to maintain the pathology (e.g., Participant C's negative affectivity predicts same-day psychoticism, and psychoticism predicts next-day negative affectivity). Each path or feature could be extracted in research contexts to examine how it associates with other variables of interest (e.g., occupational functioning).

Personalized analyses are not limited to observed variables and can be used to estimate complex latent psychological constructs of interest. In fact, some of the earliest research used factor analysis (i.e., latent variables) to study differences in the psychological structure of individuals. The classic

method of idiographic factor analysis is *p*-technique, which was developed by Cattell et al. (1947) and essentially acts as exploratory factor analysis for $n = 1$ data (Molenaar & Lo 2012). Using *p*-technique reveals the dynamic structure (number of factors and pattern of factor loadings) of an individual's multivariate time series, but the associations among factors remain contemporaneous, not lagged. Dynamic factor analysis (DFA) (Molenaar 1985, Wood & Brown 1994) extends the basic *p*-technique model to include structural paths across waves. Recently, Fisher et al. (2017, 2019) used a two-stage method of first employing *p*-technique to establish an individual's latent syndromal structure, then saving factor scores that are then used to examine lagged associations among the constructs in an approximation of DFA. These models were used to generate individualized treatment protocols for individuals with depression and anxiety. In Fisher et al.'s (2019) most recent open trial, an algorithm developed by Fernandez et al. (2017) was used to recommend which unified protocol modules (Barlow et al. 2011) were best fitted to each individual's unique psychopathology. Results of their first open trial were promising (Fisher et al. 2019), further suggesting that personalized treatments will involve the use of specialized idiographic analytic techniques. Beyond *p*-technique and DFA, extended uSEM and DSEM offer the ability to establish time-series models that include dynamic latent variables.

However, the models discussed thus far do not explicitly treat the included constructs as an integrated system, although this is often the implicit interest of a personalized model. In an effort to capture features of the whole system, researchers have been leveraging graph theory metrics and applying them to networks of associations. Note that the so-called network approach to psychopathology (Borsboom & Cramer 2013) has relied on the use of graph theory metrics but has stumbled on the path to generating novel insights precisely because of its reliance on between-person data when conceptually it seeks to describe dynamic processes (Bringmann & Eronen 2018). Most of the psychometric network literature in psychopathology reflects a failure to synchronize theory, data, and model, which is the principal goal of the personalized approach to psychopathology. For instance, Borsboom & Cramer (2013) estimated networks of associations among symptoms of clinical interview–assessed depression (assessed during worst 2-week period) and generalized anxiety disorder (assessed over the prior 6 months). This typical example pairs a within-person theory with temporally asynchronous data and a cross-sectional statistical model, precluding any theory-relevant findings—it also fails to provide person-specific parameters. However, when applied to appropriate within-person data, graph theory metrics are a promising approach to quantifying global features of the associations among time-series variables. For instance, one can estimate a density parameter to quantify how strongly connected an individual's emotions are over time. Highly dense (i.e., strong) associations might link conceptually to a poorly differentiated emotional system or to an inability to regulate emotions such that they spread widely once experienced. Pe et al. (2015), Bringmann et al. (2016), and Wigman et al. (2013) have shown that density of dynamic associations among affects within an individual over time is linked to depression, neuroticism, and severity of general psychopathology, respectively.

In the same vein, centrality metrics, which use a variety of approaches to summarize a variable's connectedness with others (e.g., strength centrality provides a sum of overall strength of associations of one variable with others), may identify key targets of intervention on the basis of the logic that changes in a critical variable may reverberate throughout the system like ripples through a pond. However, to date, direct evidence for this proposition using appropriate intensive longitudinal data has been limited (cf. Groen et al. 2019). As with all model features, it appears that centrality metrics differ substantially across participants (Fisher et al. 2017); therefore, it is plausible that they may be linked with important outcomes. However, most centrality indices were developed in different contexts (e.g., social networks, railroad tracks) and may not translate well into the psychometric data context. Researchers are therefore strongly cautioned that they should

proceed thoughtfully in this area of analysis (Bringmann et al. 2019). Other clever uses of graph theory metrics in personalized models include identifying bridges—observations from different constructs with strong associations—between patients internalizing symptom severity and psychotherapy processes (Kaiser & Laireiter 2018).

Ultimately, the models reviewed here are oft-used approaches in contemporary personalized psychopathology, but they are only a small subset of those that might be relevant for understanding an individual's pathology (Hamaker et al. 2015). Despite the impressive number of modeling options currently available, there is considerable room for improvement in matching concept to method. In particular, the field needs to do a better job of explicitly incorporating time and temporal dynamics into the models. Notably, all models that we have covered here reduce the data to contemporaneous and lagged (usually just lag-of-one time-point) associations. Moreover, they all assume stationarity and equilibrium (i.e., that the structure of the data associations and variances remains the same over the entire period of assessment). It is likely that these assumptions frequently do not hold, and we are often explicitly interested in understanding the shifts in data structure over time (e.g., critical slowing of affective processes in depression) (van de Leemput et al. 2014; but see Bos & de Jonge 2014 for a critique of this study). Thus, there is a need for models that can accommodate and even leverage nonstationarity. We anticipate that we will see increasing use of dynamical systems analysis (Hosenfeld et al. 2015; Odgers et al. 2009; Pettersson et al. 2013; Toonen et al. 2016a,b), as well as VAR models that can accommodate time-varying processes (Bringmann et al. 2018).

CAN MODELS GENERALIZE FROM INDIVIDUALS TO THE POPULATION?

Impediments to the widespread adoption of idiographic research include lack of generalizability and the difficulty of scaling up to large numbers of participants. On the one hand, the fact that personalized psychopathology models are not generalizable, and instead tailored to fit only one individual's processes, is why they are valuable (Barlow et al. 2009). On the other hand, personalized models offer direct and potentially more precise measurement of the contextualized dynamic processes that could serve as optimal building blocks for bottom-up models of psychopathology that would be generalizable (Wright 2011). Insofar as this is the case, one would ideally be able to estimate person-specific models on large enough numbers of participants to search for reliable shared features. Or, in the view Wright & Zimmermann (2019) have furthered, one could treat components of personalized models as individual difference variables that can be understood to have their own distributions in the population. However, this is very difficult to do if each model is painstakingly handcrafted. Thus, in order to achieve some degree of generalizability, specifically a quantitative integration across multiple person-specific models, routines for rapidly developing individualized models and integrating across individuals are necessary.

Automatic individual model selection is now relatively easily achievable using open-source and customizable software, such as R (see **http://www.R-project.org/**). In essence, one needs to establish a set of model-fitting and selection rules that can be applied to each participant's data, and then automate the procedure across multiple participants. These could include approaches such as using parallel analysis or the minimum average partial test to determine the number of factors to retain in *p*-technique/DFA, automatic searches for significant (e.g., $p < 0.05$) regression paths in uSEM, or regularization in a network model, to name a few.

Some models (or model features, to be more exact) are easier to integrate than others. And how one approaches achieving generalizable conclusions depends on the goal of integration. For instance, in the tradition of single-case experimental design research, the goal is often to

demonstrate replicability of an identified process (Barlow et al. 2009). A general conclusion about whether such a process exists has been determined by meta-analysis (Barton et al. 2019). However, what might seem like a straightforward procedure is often challenging because person-specific effect sizes can vary as a function of model design features (Pustejovsky 2018). When it comes to latent variable models, individual models may defy direct averaging due to qualitative differences across individuals (e.g., one- versus three-factor models). Therefore, one approach to automation might be to seek out individuals with apparent differences in structures and cluster them (de Roover et al. 2013). A challenge, of course, is that cluster- or class-based solutions rarely identify truly homogeneous groups and are best used as heuristics. In this context, though, this type of clustering may prove useful for moving to the next stage of understanding key processes by reducing heterogeneity through identifying individuals with similar features. An alternative approach is to assume that the same latent processes exist across individuals but allow for individual differences in the details of the measurement models (i.e., factor loadings), in what has been called the idiographic filter (Molenaar & Nesselroade 2012, Nesselroade et al. 2007). Each of these approaches clearly targets different levels of the personalization hierarchy.

More recently, Group Iterative Multiple Model Estimation (GIMME) (Gates & Molenaar 2012, Lane et al. 2019) has been proposed as an innovative method for bridging the idiographic–nomothetic divide. GIMME is ultimately a person-specific approach, because it estimates an idiographic model from each individual's data, but it also seeks out and prioritizes for estimation those features that are present in most of the sample. This process is iterative, such that the algorithm first estimates each individual's model, and if there are paths that are present in the majority of the sample (the user specifies what the threshold for majority is), these are then freely estimated in all models in subsequent runs until all group paths are identified. Then, in a final run, each individual's model is estimated, allowing for additional features that are unique to each individual (or at least not shared by the majority). GIMME was initially designed for fMRI data and uses the extended uSEM as the model that is fitted to each individual, using an automated search to determine which paths to free. The models shown in **Figure 2** were estimated using GIMME, and as noted, all share the effect of stress on hostility. This would be a group path (but note that the strength of this shared path is uniquely estimated in each personalized model), whereas the others would be considered person-specific nuances. A benefit of this approach is that a given individual's model can be understood in the context of the larger sample—for example, telling clinicians whether a client's presentation has any particularly distinct features that would be ideal for intervention, such as prominent contemporaneous and lagged effects of catastrophizing in a patient with major depressive disorder. Although GIMME is relatively novel, it has been used in contexts as diverse as fMRI research (for which it was originally developed; Gates & Molenaar 2012), sleep and affect processes in depression (Bouwmans et al. 2018), and daily behavioral processes in personality pathology (Wright et al. 2019).

In its current version, GIMME can estimate uSEM-based models that include clustering (along with subgroup-specific paths), exogenous variables (e.g., stress and time in **Figure 2**), and person-specific latent variable estimation (Gates et al. 2020). There are several additional features that go beyond the scope of this review. We emphasize that the innovation that went into GIMME extends beyond its current instantiation and could conceivably be applied to any number of relevant base models (e.g., gVAR). The key is that it leverages information from multiple individuals to arrive at a more robust model for each individual. Despite the promise of GIMME and other approaches reviewed here, the challenge of moving beyond the individual model to generate large-scale conclusions, especially in research contexts, is likely to be a major source of growth in personalized models of psychopathology in the future.

IS THE GOAL TO EXPLAIN OR TO PREDICT?

The literature reviewed above on personalized models of psychopathology has, with few exceptions, adopted an explanatory approach. That is, the research has primarily sought to explain the causal mechanisms that drive behavior. This is typical of the vast majority of psychological research, but it can be contrasted with a predictive approach, where the priority is accurately detecting or predicting behavior and understanding the underlying mechanisms is secondary (Yarkoni & Westfall 2017). Predictive approaches tend to leverage big data and use machine learning models, some of which obscure the associations among observed variables. The ability to collect large quantities of data via intensive repeated measurements opens up possibilities for predictive approaches in personalized psychopathology research and practice. Adopting a predictive lens involves endorsing that it is more important to know when a behavior will occur than why. For many applications, this will be a worthwhile trade-off: If the goal is to intervene on a behavior, being able to forecast and prevent may be the most valuable capability. The calculus becomes tricky when knowing why a behavior is occurring is a prerequisite for effective intervention. Yarkoni & Westfall (2017) argue that investing more in prediction over the traditional investment in explanation might yield new understanding as a by-product.

Prediction-based science is relatively new to psychology but is standard practice in other scientific fields. There is, however, a growing body of research using predictive techniques for personalization, mostly in the service of better treatment outcomes, such as prediction of best-fit treatment paradigm (Cohen & DeRubeis 2018), prediction of likely early dropouts in treatment (Lutz et al. 2018), and prediction of compliance with ambulatory assessment protocols (Boukhechba et al. 2018). Note that the approach promoted by Cohen & DeRubeis (2018) uses personalization in a different way than we do here, relying primarily on between-person data to predict treatment outcome but not to build a personalized model for each individual. Other research has sought to build personalized models to predict a specific behavior like smoking (Fisher & Soyster 2019), medical symptom complaints (Low et al. 2017), and medical readmission (Doryab et al. 2019). Psychological research is likely to continue to be dominated by explanatory studies, but the example predictive studies suggest that predictive modeling is a promising alternative that is aligned with the personalized approach to psychopathology.

HOW IS PERSONALIZED PSYCHOPATHOLOGY CURRENTLY BEING USED?

Our review has thus far prioritized definitional issues along with conceptual and methodological foundations. This reflects the fact that the body of research on personalized models of psychopathology is unified in a perspective and approach to understanding mental disorder, not a shared target of inquiry or specific topic. Recently, however, many different laboratories have adopted this approach and applied it to diverse questions. Many of the emerging papers might best be understood as proof of concept or descriptive in nature. These studies often fit personalized models to intensive data from multiple participants in order to demonstrate their feasibility and characterize the heterogeneity of the models (e.g., de Vos et al. 2017; Fisher 2015; Fisher et al. 2017; Stavrakakis et al. 2015; Wright et al. 2016, 2019). A consistent finding emerging from this descriptive body of research is that heterogeneity across individuals is the rule, rather than the exception. This is, of course, the fundamental reason to pursue personalized models. For instance, in a GIMME model of 96 outpatients with personality disorders (Wright et al. 2019), only the link between stress and negative affect was shared by the majority of individuals. All other paths among affect, interpersonal behavior, stress, and daily functioning were found in a minority of

individuals. Some research in this vein has focused on comparing the personalized models of a clinical group (e.g., those with depression) and healthy controls (Booij et al. 2015, 2016; Bouwmans et al. 2015, 2018). Although thus far limited in samples and scope, the results suggest that, despite high degrees of individual heterogeneity in model features, some features distinguish clinical cases. Other research has accepted this heterogeneity as a given and moved toward implementing personalized assessment and feedback. For example, one research group has developed a system for providing population-scale personalized feedback from participant-provided ambulatory assessment data (Blaauw et al. 2014, 2017; Bos et al. 2018; van der Krieke et al. 2015, 2016). The size and ambition of this study are remarkable, although the feedback was post hoc and not intended as an intervention per se; therefore, much remains to be learned about differential effects of personalized feedback.

Unsurprisingly, the bulk of applied personalized psychopathology research is aimed at improving assessment of treatment outcomes. For example, recent work has sought to develop client-specific outcome measures and client-specific markers of treatment progress (Jones & Hurrell 2019, Kaiser & Laireiter 2018, Smith et al. 2015). Other research has selected one or two cases to illustrate how personalized assessment and modeling might work in clinical practice for developing case conceptualization or feedback (e.g., Hopwood et al. 2016; Kroeze et al. 2017; Lewis & Ridenour 2019; Mumma 2004; Mumma & Mooney 2007a,b; Roche et al. 2014). In addition, personalized models of psychopathology have been used to understand change during treatment (Boswell et al. 2014, Boswell & Bugatti 2016, Hartogs et al. 2017, Hoenders et al. 2012) and to personalize treatments (Bosley et al. 2018, Boswell & Bugatti 2016, Boswell & Schwartzman 2018, Brake et al. 2016, Fisher & Boswell 2016, Fisher et al. 2019, Kramer et al. 2014). In a decidedly extreme example, van Roekel et al. (2017) used personalized assessments to prescribe skydiving in an effort to jump-start participants' positive affect. One research group has reported on a semiautomated process that includes both developing personalized models and generating suggestions for best-fit interventions to target key symptoms of the internalizing disorders (i.e., depression and anxiety) (Fernandez et al. 2017, Rubel et al. 2018). As noted above, the first open trial using this method (Fisher et al. 2019) resulted in large average improvements, but without a comparison group it is unclear whether personalization will lead to faster or larger improvements.

WHAT ARE THE MAJOR CHALLENGES AND FUTURE DIRECTIONS FOR PERSONALIZED MODELS OF PSYCHOPATHOLOGY?

Despite ardent and broadening enthusiasm for personalized models of psychopathology, several major challenges lie ahead. For one, serious consideration of personalizing psychopathology models raises the question of whether they will capture idiosyncratic manifestations of the same pathology (surface personalization) or truly individualized processes (deep personalization). Some long-standing idiographic traditions, such as behavior analysis, explicitly assume that processes are shared across individuals and that individuals differ merely in their idiosyncratic manifestations. Trivially, one individual's phobia happens to be of dogs, whereas the next person's is of spiders. This would be a surface distinction. Less obvious is that, though all organisms may share the negative reinforcement process, one person's maladaptive negative reinforcement process may stem from substance withdrawal (i.e., substance-use disorder) while another may manifest as avoidance (i.e., social anxiety disorder). The opposite may also be true, and similarities in observable behavior or clinical complaints belie fundamentally distinct mechanisms. For example, risky or problematic alcohol use may be driven by positive or negative reinforcement processes: Some individuals drink to feel good; some individuals drink to avoid feeling bad. Indeed, heterogeneity in problematic alcohol use has led to calls for personalized models (Litten et al. 2015). What is also clear is that

many severe and persistent forms of psychopathology are so vexing precisely because they lead to seemingly paradoxical processes, such as the insecurely attached individual who threatens their partner or puts them in dangerous situations in an effort to ensure they do not leave, seemingly guaranteeing the opposite effect.

The contemporary personalization of psychopathology literature has not yet formally addressed this question of deep versus surface-level heterogeneity, even while often implying the potential for deep heterogeneity when arguing for the need for personalization. We believe that this question will require thoughtful consideration moving forward, with explication of what might constitute equivalencies as well as quantitative and qualitative differences in processes across individuals (Wright 2011). As the personalized approach matures and moves from exploratory to confirmatory work, it will be necessary to design studies that can adjudicate between deep and surface-level heterogeneity. The answer to the question is important for designing assessments, analyzing data, and interpreting resulting models for intervention.

An extension of this question is: How deep should one go with the idiographic nature of the models? Starting from the top, across individuals one could use the same constructs as indicated by the same items, or fit unique factor structures to each individual, or use tailor-written items. In our review, we have found examples of each of these levels of personalization. Which is most appropriate may differ by context and goals, and there is an implied trade-off of complexity for potential precision. However, it may be possible to provide studies of incremental validity gained at differing levels of personalization (e.g., would one find larger effect sizes with personalized items?) that can be compared with other considerations like burden, interpretability, generalizability, and user comfort. We do not wish to suggest one best approach at this time, but rather emphasize that systematic inquiry is necessary.

Some of the challenges facing personalized assessments and modeling are those facing all of intensive longitudinal research, including the poor temporal resolution of our theories (on what timescale does the process of interest play out?), difficulty linking variables that occur on different timescales (sleep occurs once a day, stressors are intermittent, and affect fluctuates constantly), and how intensively and for how long assessments are needed to achieve a reliable individual model. Currently, relatively few systematic investigations have examined the minimum amount of evidence needed to achieve acceptable reliability or the expected stability of assessments over time (Beck & Jackson 2019). The ambulatory assessment literature, which currently has a strong influence on the personalized approach literature, has not invested sufficiently in the basic methodological research necessary to answer these questions, even though they have implications for meeting basic standards of clinical assessments in applied settings (Wright & Zimmermann 2019).

In our review of the statistical techniques used to create personalized models, we have alluded to the fact that the popular tools were some variation of either VAR or *p*-technique, or both. However, despite some surface similarities, different research groups are approaching the implementation and interpretation of these models in very different ways. In a telling study, Bastiaansen et al. (2019) gave the same multivariate time series of a single patient's data to 12 research groups and asked them to analyze the data and arrive at a hypothetical treatment recommendation. Although some similarities reflective of the general trends summarized above were observed (e.g., most teams used a VAR model), no two teams arrived at the same final personalized model or the same recommended treatment targets. This result suggests that much work is needed to develop standardized procedures for personalized models that can be reliably implemented in different labs. Furthermore, these procedures must be validated against outcome benchmarks to show which decisions affect the ultimate interpretation and utility of a model. These procedures likely need to include each step of the process, from battery selection to data collection to statistical modeling.

Some research has examined the impact of selecting different models on clinical inferences (e.g., Ridenour et al. 2013), but more such work is sorely needed.

Ultimately, for personalized models to secure a place at the crowded table of different approaches to conceptualize, assess, and develop treatment recommendations for psychopathology, they need to demonstrate that they provide incremental validity and utility over current methods. Although we know this is obvious, we believe it must be stated clearly. Most of the literature reviewed above promotes the method and its promise, but rarely is its value directly tested against established approaches (e.g., cross-sectional self-report). Given the burden placed on patients and practitioners, implementing personalized assessments in clinical practice will require demonstration of improved outcomes. Particularly, studies are needed that compare the availability of personalized assessment results to assessments as usual and evaluate the effect on outcomes. To be fair, the vast majority of the assessment literature has failed to engage in this basic test of utility validity. More knowledge is presumed to lead to better outcomes, but that cannot be taken on faith. The calculation may be different in research settings, because personalized modeling may hold incremental value that can be translated into other gains in understanding and conceptualization of psychopathology that may not ultimately require burdensome assessments in practice.

Despite the need to demonstrate the validity and incremental utility of personalized models of psychopathology, we do not wish to end on a negative note. What is clear from reviewing the rapidly growing literature is that its bright enthusiasm stems from the fact that clinical scientists can see clear links between the methods and the clinical realities of assessing and treating an individual with psychological problems. Individuals are dynamic, their behavior is contextualized, and clinically the effort is spent on changing the functional processes that drive this behavior. The methods reviewed here promise to bridge the research–practice divide in ways that until only recently seemed elusive. Despite the challenges associated with aspects like burden, personalized assessments hold the unique ability to allow patients and participants to feel deeply understood due to the intensity and depth of assessment. Additionally, they open up new types of intervention, such as just-in-time adaptive interventions, that could revolutionize the psychopathology treatment landscape and would be available only with this approach to assessing and modeling psychopathology. The challenges are large but also directly addressable, and we encourage researchers interested in this area to take some of them up in their next study. Ultimately, humans are complexes of mutually influencing systems whose processes serve an operative role in maintaining their functioning and health, and the personalized approach to psychopathology works to treat the whole complex as the unit of analysis.

SUMMARY POINTS

1. Psychiatric diagnoses do a poor job of describing any given patient's psychopathology, and individuals present with highly heterogeneous issues.
2. The personalized modeling approach to psychopathology conceptualizes psychopathology as a complex system of contextualized dynamic processes that is nontrivially specific to each individual.
3. An individual's processes can be approximated with a formal idiographic (i.e., personalized) statistical model.
4. Personalized models of psychopathology use intensive repeated measurements to collect enough data for an individual to estimate a model of their specific processes.

5. Advances in data collection, computation, and automation of statistical procedures enable scalability, the limits of which previously hampered idiographic research.
6. Integration across individuals to establish generalizable features and inferences remains challenging, although several promising options are now available.
7. Personalization of assessment is a matter of degree, ranging from standardized assessment batteries to surveys with patient-specific wording.
8. The extant research shows that individual models of psychopathology result in highly heterogeneous patterns that are a mix of shared and unique features.

FUTURE ISSUES

1. Research is needed to demonstrate the incremental validity of personalized models of psychopathology with respect to important outcomes like treatment gains.
2. Systematic research is needed into the effect of model specification decisions on inferences.
3. Further development and dissemination of models that do not assume the same process over time (i.e., are nonstationary) are needed.
4. Whether personalized models capture deep or surface-level processes remains poorly understood.
5. Research is needed on the acceptability of personalized modeling procedures by patients and clinicians.
6. The use of personalized models to develop just-in-time adaptive interventions is a promising area for future research.

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LITERATURE CITED

Allport G. 1937. *Personality: A Psychological Interpretation*. Oxford, UK: Holt

APA (Am. Psychiatr. Assoc.). 1980. *Diagnostic and Statistical Manual of Mental Disorders*. Washington, DC: Am. Psychiatr. Publ. 3rd ed.

Asaparouhov T, Hamaker EL, Muthén B. 2018. Dynamic structural equation models. *Struct. Equ. Model.* 25:359–88

Bae S, Chung T, Ferreira D, Dey AK, Suffoletto B. 2018. Mobile phone sensors and supervised machine learning to identify alcohol use events in young adults: implications for just-in-time adaptive interventions. *Addict. Behav.* 83:42–47

Barlow DH, Farchione TJ, Fairholme CP, Ellard KK, Boisseau CL, et al. 2011. *Unified Protocol for Transdiagnostic Treatment of Emotional Disorders: Therapist Guide*. New York: Oxford Univ. Press

Barlow DH, Nock M, Hersen M. 2009. *Single Case Experimental Designs: Strategies for Studying Behavior for Change*. Boston: Allyn & Bacon. 3rd ed.

Barton EE, Meadan H, Fettig A. 2019. Comparison of visual analysis, non-overlap methods, and effect sizes in the evaluation of parent implemented functional assessment based interventions. *Res. Dev. Disabil.* 85:31–41

Bastiaansen JA, Kunkels YK, Blaauw F, Boker SM, Ceulemans E, et al. 2019. Time to get personal? The impact of researchers' choices on the selection of treatment targets using the experience sampling methodology. PsyArXiv. **https://doi.org/10.31234/osf.io/c8vp7**

Beck AT, Rush AJ, Shaw BF, Emery G. 1979. *Cognitive Therapy of Depression*. New York: Guilford

Beck E, Jackson JJ. 2019. Consistency and change in idiographic personality: a longitudinal ESM network study. *J. Personal. Soc. Psychol.* In press. **https://doi.org/10.1037/pspp0000249**

Beltz AM, Wright AGC, Sprague BN, Molenaar PCM. 2016. Bridging the nomothetic and idiographic approaches to the analysis of clinical data. *Assessment* 23:447–58

Bentley KH, Kleiman EM, Elliott G, Huffman JC, Nock MK. 2018. Real-time monitoring technology in single-case experimental design research: opportunities and challenges. *Behav. Res. Ther.* 117:87–96

Blaauw FJ, Schenk HM, Jeronimus BF, van der Krieke L, de Jonge P, et al. 2016. Let's get Physiqual—an intuitive and generic method to combine sensor technology with ecological momentary assessments. *J. Biomed. Inf.* 63:141–49

Blaauw FJ, van der Krieke L, Bos E, Emerencia A, Jeronimus BF, et al. 2014. HowNutsAreTheDutch: personalized feedback on a national scale. In *Proceedings of the AAAI 2014 Fall Symposium Series*, pp. 6–10. Menlo Park, CA: AAAI

Blaauw FJ, van der Krieke L, Emerencia AC, Aiello A. 2017. Personalized advice for enhancing well-being using automated impulse response analysis. arXiv:1706.09268 [cs]

Booij SH, Bos EH, Bouwmans ME, Faassen MV, Kema IP, et al. 2015. Cortisol and α-amylase secretion patterns between and within depressed and non-depressed individuals. *PLOS ONE* 10:e0131002

Booij SH, Bos EH, de Jonge P, Oldehinkel AJ. 2016. The temporal dynamics of cortisol and affective states in depressed and non-depressed individuals. *Psychoneuroendocrinology* 69:16–25

Borsboom D, Cramer AO. 2013. Network analysis: an integrative approach to the structure of psychopathology. *Annu. Rev. Clin. Psychol.* 9:91–121

Bos EH, de Jonge P. 2014. "Critical slowing down in depression" is a great idea that still needs empirical proof. *PNAS* 111:e878

Bos EH, Hoenders R, de Jonge P. 2012. Wind direction and mental health: a time-series analysis of weather influences in a patient with anxiety disorder. *BMJ Case Rep.* 2012:bcr2012006300

Bos FM, Blaauw FJ, Snippe E, van der Krieke L, de Jonge P, Wichers M. 2018. Exploring the emotional dynamics of subclinically depressed individuals with and without anhedonia: an experience sampling study. *J. Affect. Disord.* 228:186–93

Bosley HG, Fisher AJ, Taylor CB. 2018. Differential responses of positive affect, negative affect, and worry in CBT for generalized anxiety disorder: a person-specific analysis of symptom course during therapy. *Psychother. Res.* 28:630–42

Boswell JF, Anderson LM, Barlow DH. 2014. An idiographic analysis of change processes in the unified transdiagnostic treatment of depression. *J. Consult. Clin. Psychol.* 82:1060–71

Boswell JF, Bugatti M. 2016. An exploratory analysis of the impact of specific interventions: Some clients reveal more than others. *J. Couns. Psychol.* 63:710–20

Boswell JF, Schwartzman CM. 2018. An exploration of intervention augmentation in a single case. *Behav. Modif.* **https://doi.org/10.1177/0145445518796202**

Boukhechba M, Cai L, Chow PI, Fua K, Gerber MS, et al. 2018. Contextual analysis to understand compliance with smartphone-based ecological momentary assessment. In *Proceedings of the 12th EAI International Conference on Pervasive Computing Technologies for Healthcare*, pp. 232–38. New York: ACM

Bouwmans ME, Beltz AM, Bos EH, Oldehinkel AJ, de Jonge P, Molenaar PC. 2018. The person-specific interplay of melatonin, affect, and fatigue in the context of sleep and depression. *Personal. Individ. Differ.* 123:163–70

Bouwmans ME, Bos EH, Booij SH, Faassen MV, Oldehinkel AJ, de Jonge P. 2015. Intra- and inter-individual variability of longitudinal daytime melatonin secretion patterns in depressed and non-depressed individuals. *Chronobiol. Int.* 32:441–46

Brake CA, Sauer-Zavala S, Boswell JF, Gallagher MW, Farchione TJ, Barlow DH. 2016. Mindfulness-based exposure strategies as a transdiagnostic mechanism of change: an exploratory alternating treatment design. *Behav. Ther.* 47:225–38

Brandt PT, Williams JT. 2006. *Multiple Time Series Models*. Thousand Oaks, CA: Sage

Bringmann LF, Elmer T, Epskamp S, Krause R, Schoch D, et al. 2019. What do centrality measures measure in psychological networks? *J. Abnorm. Psychol.* 128:892–903

Bringmann LF, Eronen MI. 2018. Don't blame the model: reconsidering the network approach to psychopathology. *Psychopathology* 125:606–15

Bringmann LF, Ferrer E, Hamaker EL, Borsboom D, Tuerlinckx F. 2018. Modeling nonstationary emotion dynamics in dyads using a time-varying vector-autoregressive model. *Multivar. Behav. Res.* 53:293–314

Bringmann LF, Pe ML, Vissers N, Ceulemans E, Borsboom D, et al. 2016. Assessing temporal emotion dynamics using networks. *Assessment* 23:425–35

Brose A, Voelkle MC, Lövdén M, Lindenberger U, Schmiedek F. 2015. Differences in the between-person and within-person structures of affect are a matter of degree. *Eur. J. Personal.* 29:55–71

Cattell RB, Cattell AKS, Rhymer RM. 1947. P-technique demonstrated in determining psychophysiological source traits in a normal individual. *Psychometrika* 12:267–88

Clarkin JF, Yeomans FE, Kernberg OF. 2006. *Psychotherapy for Borderline Personality: Focusing on Object Relations*. Washington, DC: Am. Psychiatr. Publ.

Cohen ZD, DeRubeis RJ. 2018. Treatment selection in depression. *Annu. Rev. Clin. Psychol.* 14:209–36

Collins FS, Varmus H. 2015. A new initiative on precision medicine. *N. Engl. J. Med.* 372:793–95

Conner TS, Tennen H, Fleeson W, Barrett LF. 2009. Experience sampling methods: a modern idiographic approach to personality research. *Soc. Personal. Psychol. Compass* 3:292–313

Costa PT, McCrae RR. 2008. The Revised NEO Personality Inventory (NEO-PI-R). In *The SAGE Handbook of Personality Theory and Assessment*, Vol. 2, ed. GJ Boyle, G Matthews, DH Saklofske, pp. 179–98. Thousand Oaks, CA: Sage

David SJ, Marshall AJ, Evanovich EK, Mumma GH. 2018. Intraindividual dynamic network analysis: implications for clinical assessment. *J. Psychopathol. Behav. Assess.* 40:235–48

de Roover K, Ceulemans E, Timmerman ME, Nezlek JB, Onghena P. 2013. Modeling differences in the dimensionality of multiblock data by means of clusterwise simultaneous component analysis. *Psychometrika* 78:648–68

de Vos SD, Wardenaar KJ, Bos EH, Wit EC, Bouwmans ME, de Jonge P. 2017. An investigation of emotion dynamics in major depressive disorder patients and healthy persons using sparse longitudinal networks. *PLOS ONE* 12:e0178586

Doryab A, Dey AK, Kao G, Low C. 2019. Modeling biobehavioral rhythms with passive sensing in the wild: a case study to predict readmission risk after pancreatic surgery. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 3:8

Dotterer HL, Beltz AM, Foster KT, Simms LJ, Wright AGC. 2019. Personalized models of personality disorders: using a temporal network method to understand symptomatology and daily functioning in a clinical sample. *Psychol. Med.* In press. **https://doi.org/10.1017/S0033291719002563**

Edershile EA, Woods WC, Sharpe BM, Crowe ML, Miller JD, Wright AGC. 2019. A day in the life of Narcissus: measuring narcissistic grandiosity and vulnerability in daily life. *Psychol. Assess.* 31:913–24

Elliott R, Wagner J, Sales C, Rodgers B, Alves P, Café MJ. 2016. Psychometrics of the personal questionnaire: a client-generated outcome measure. *Psychol. Assess.* 28:263–78

Epskamp S, Borkulo CV, Veen DC, Servaas M, Isvoranu A, et al. 2018. Personalized network modeling in psychopathology: the importance of contemporaneous and temporal connections. *Clin. Psychol. Sci.* 6:416–27

Fernandez KC, Fisher AJ, Chi C. 2017. Development and initial implementation of the dynamic assessment treatment algorithm (DATA). *PLOS ONE* 12:e0178806

Fisher AJ. 2015. Toward a dynamic model of psychological assessment. *J. Consult. Clin. Psychol.* 83:825–36
Fisher AJ, Bosley HG, Fernandez KC, Reeves JW, Diamond AE, et al. 2019. Open trial of a personalized modular treatment for mood and anxiety. *Behav. Res. Ther.* 116:69–79
Fisher AJ, Boswell JF. 2016. Enhancing the personalization of psychotherapy with dynamic assessment and modeling. *Assessment* 23:496–506
Fisher AJ, Reeves JW, Lawyer G, Medaglia JD, Rubel JA. 2017. Exploring the idiographic dynamics of mood and anxiety via network analysis. *J. Abnorm. Psychol.* 126:1044–56
Fisher AJ, Soyster PD. 2019. Generating accurate personalized predictions of future behavior: a smoking exemplar. PsyArXiv. **https://doi.org/10.31234/osf.io/e24v6**
Ganz JB, Ayres KM. 2018. Methodological standards in single-case experimental design: raising the bar. *Res. Dev. Disabil.* 79:3–9
Gates KM, Fisher ZF, Bollen KA. 2020. Latent variable GIMME using model implied instrumental variables (MIIVs). *Psychol. Methods* 25:227–42
Gates KM, Molenaar PCM. 2012. Group search algorithm recovers effective connectivity maps for individuals in homogeneous and heterogeneous samples. *NeuroImage* 63:310–19
Groen RN, Snippe E, Bringmann LF, Simons CJP, Hartmann JA, et al. 2019. Capturing the risk of persisting depressive symptoms: a dynamic network investigation of patients' daily symptom experiences. *Psychiatr. Res.* 271:640–48
Hamaker EL, Ceulemans E, Grasman RPPP, Tuerlinckx F. 2015. Modeling affect dynamics: state of the art and future challenges. *Emot. Rev.* 7:316–22
Hamaker EL, Schuurman NK, Zijlmans EAO. 2017. Using a few snapshots to distinguish mountains from waves: weak factorial invariance in the context of trait-state research. *Multivar. Behav. Res.* 52:47–60
Hamaker EL, Wichers M. 2017. No time like the present: discovering the hidden dynamics in intensive longitudinal data. *Curr. Dir. Psychol. Sci.* 26:10–15
Hamilton JD, Kendall PC, Gosch E, Furr JM, Sood E. 2008. Flexibility within fidelity. *J. Am. Acad. Child Adolesc. Psychol.* 47:987–93
Hartogs BM, Ploeg KV, Bos EH, Bartels-Velthuis AA. 2017. Heart rate variability biofeedback stress relief program for depression. *Methods Inf. Med.* 56:419–26
Hayes SC, Hofmann SG, Stanton CE, Carpenter JK, Sanford BT, et al. 2019. The role of the individual in the coming era of process-based therapy. *Behav. Res. Ther.* 117:40–53
Hayes SC, Strosahl KD, Wilson KG. 2012. *Acceptance and Commitment Therapy: The Process and Practice of Mindful Change*. New York: Guilford. 2nd ed.
Haynes SN, Mumma GH, Pinson C. 2009. Idiographic assessment: conceptual and psychometric foundations of individualized behavioral assessment. *Clin. Psychol. Rev.* 29:179–91
Himmelstein PH, Woods WC, Wright AGC. 2019. A comparison of signal- and event-contingent ambulatory assessment of interpersonal behavior and affect in social situations. *Psychol. Assess.* 31:952–60
Hoenders HR, Bos EH, de Jong JTM, de Jonge P. 2012. Temporal dynamics of symptom and treatment variables in a lifestyle-oriented approach to anxiety disorder: a single-subject time-series analysis. *Psychother. Psychosom.* 81:253–55
Hofmann SG, Hayes SC. 2019a. The future of intervention science: process-based therapy. *Clin. Psychol. Sci.* 7:37–50
Hofmann SG, Hayes SC. 2019b. Functional analysis is dead: Long live functional analysis. *Clin. Psychol. Sci.* 7:63–67
Hopwood CJ, Thomas KM, Luo X, Bernard N, Lin Y, Levendosky AA. 2016. Implementing dynamic assessments in psychotherapy. *Assessment* 23:507–17
Hosenfeld B, Bos EH, Wardenaar KJ, Conradi HJ, van der Maas HLJ, et al. 2015. Major depressive disorder as a nonlinear dynamic system: bimodality in the frequency distribution of depressive symptoms over time. *BMC Psychiatry* 15:222
Hyman SE. 2010. The diagnosis of mental disorders: the problem of reification. *Annu. Rev. Clin. Psychol.* 6:155–79
Insel TR. 2014. The NIMH Research Domain Criteria (RDoC) project: precision medicine for psychiatry. *Am. J. Psychiatry* 171:395–97

Jameson JL, Longo DL. 2015. Precision medicine—personalized, problematic, and promising. *N. Engl. J. Med.* 372:2229–34
Jones S, Hurrell E. 2019. A single case experimental design: How do different psychological outcome measures capture the experience of a client undergoing CBT for chronic pain? *Br. J. Pain* 13:6–12
Kaiser T, Laireiter A-R. 2018. Process-symptom-bridges in psychotherapy: an idiographic network approach. *J. Pers.-Oriented Res.* 4:49–62
Kim J, Zhu W, Chang L, Bentler PM, Ernst T. 2007. Unified structural equation modeling approach for the analysis of multisubject, multivariate functional MRI data. *Hum. Brain Mapp.* 28:85–93
Kotov R, Krueger RF, Watson D, Achenbach TM, Althoff RR, et al. 2017. The Hierarchical Taxonomy of Psychopathology (HiTOP): a dimensional alternative to traditional nosologies. *J. Abnorm. Psychol.* 126:454–77
Kramer I, Simons CJ, Hartmann JA, Menne-Lothmann C, Viechtbauer W, et al. 2014. A therapeutic application of the experience sampling method in the treatment of depression: a randomized controlled trial. *World Psychiatry* 13:68–77
Kroeze R, Veen DC, Servaas MN, Bastiaansen JA, Voshaar RC, et al. 2017. Personalized feedback on symptom dynamics of psychopathology: a proof-of-principle study. *J. Pers.-Oriented Res.* 3:1–10
Kuyken W, Padesky CA, Dudley R. 2011. *Collaborative Case Conceptualization: Working Effectively with Clients in Cognitive–Behavioral Therapy*. New York: Guilford
Lane ST, Gates KM, Pike HK, Beltz AM, Wright AGC. 2019. Uncovering general, shared, and unique temporal patterns in ambulatory assessment data. *Psychol. Methods* 24:54–69
Lee CM, Cronce JM, Baldwin SA, Fairlie AM, Atkins DC, et al. 2017. Psychometric analysis and validity of the daily alcohol-related consequences and evaluations measure for young adults. *Psychol. Assess.* 29:253–63
Lewis KC, Ridenour JM. 2019. The integration of EMA and single-occasion multimethod assessment data for a complex psychiatric patient. *Assessment*. In press. **https://doi.org/10.1177/1073191118825313**
Litten RZ, Ryan ML, Falk DE, Reilly M, Fertig JB, Koob GF. 2015. Heterogeneity of alcohol use disorder: understanding mechanisms to advance personalized treatment. *Alcohol. Clin. Exp. Res.* 39:579–84
Linehan M. 1993. *Cognitive–Behavioral Treatment of Borderline Personality Disorder*. New York: Guilford
Low CA, Dey AK, Ferreira D, Kamarck T, Sun W, et al. 2017. Estimation of symptom severity during chemotherapy from passively sensed data: exploratory study. *J. Med. Internet Res.* 19:e420
Lutz W, Schwartz B, Hofmann SG, Fisher AJ, Husen K, Rubel JA. 2018. Using network analysis for the prediction of treatment dropout in patients with mood and anxiety disorders: a methodological proof-of-concept study. *Sci. Rep.* 8:7819
Mohr DC, Zhang M, Schueller SM. 2017. Personal sensing: understanding mental health using ubiquitous sensors and machine learning. *Annu. Rev. Clin. Psychol.* 13:23–47
Molenaar PCM. 1985. A dynamic factor model for the analysis of multivariate time series. *Psychometrika* 50:181–202
Molenaar PCM. 2004. A manifesto on psychology as idiographic science: bringing the person back into scientific psychology, this time forever. *Meas. Interdiscip. Res. Perspect.* 2:201–18
Molenaar PCM, Campbell CG. 2009. The new person-specific paradigm in psychology. *Curr. Dir. Psychol. Sci.* 18:112–17
Molenaar PCM, Lo L. 2012. Dynamic factor analysis and control of developmental processes. In *Handbook of Developmental Research Methods*, ed. B Laursen, TD Little, NA Card, pp. 333–49. New York: Guilford
Molenaar PCM, Nesselroade JR. 2012. Merging the idiographic filter with dynamic factor analysis to model process. *Appl. Dev. Sci.* 16:210–19
Mumma GH. 2004. Validation of idiosyncratic cognitive schema in cognitive case formulations: an intraindividual idiographic approach. *Psychol. Assess.* 16:211–30
Mumma GH, Fluck J. 2016. How valid is your case formulation? Empirically testing your cognitive behavioural case formulation for tailored treatment. *Cogn. Behav. Ther.* 9:e12
Mumma GH, Marshall AJ, Mauer C. 2018. Person-specific validation and testing of functional relations in cognitive–behavioural case formulation: guidelines and options. *Clin. Psychol. Psychother.* 25:672–91
Mumma GH, Mooney SR. 2007a. Comparing the validity of alternative cognitive case formulations: a latent variable, multivariate time series approach. *Cogn. Ther. Res.* 31:451–81

Mumma GH, Mooney SR. 2007b. Incremental validity of cognitions in a clinical case formulation: an intraindividual test in a case example. *J. Psychopathol. Behav. Assess.* 29:17–28

Nesselroade JR, Gerstorf D, Hardy SA, Ram N. 2007. Idiographic filters for psychological constructs. *Measurement* 5:217–35

Norcross JC, Wampold BE. 2011. What works for whom: tailoring psychotherapy to the person. *J. Clin. Psychol.* 67:127–32

Odgers CL, Mulvey EP, Skeem JL, Gardner W, Lidz CW, Schubert C. 2009. Capturing the ebb and flow of psychiatric symptoms with dynamical systems models. *Am. J. Psychiatry* 166:575–82

Pe ML, Kircanski K, Thompson RJ, Bringmann LF, Tuerlinckx F, et al. 2015. Emotion-network density in major depressive disorder. *Clin. Psychol. Sci.* 3:292–300

Pew Res. Cent. 2019. *Mobile fact sheet*. Pew Res. Cent., Washington, DC. **https://www.pewinternet.org/fact-sheet/mobile/**

Pettersson E, Boker SM, Watson D, Clark LA, Tellegen A. 2013. Modeling daily variation in the affective circumplex: a dynamical systems approach. *J. Res. Personal.* 47:57–69

Piccirillo ML, Rodebaugh TL. 2019. Foundations of idiographic methods in psychology and applications for psychotherapy. *Clin. Psychol. Rev.* 71:90–100

Price RB, Lane S, Gates K, Kraynak TE, Horner MS, et al. 2017. Parsing heterogeneity in the brain connectivity of depressed and healthy adults during positive mood. *Biol. Psychiatry* 81:347–57

Pustejovsky JE. 2018. Procedural sensitivities of effect sizes for single-case designs with directly observed behavioral outcome measures. *Psychol. Methods* 24:217–35

Reber R, Canning EA, Harackiewicz JM. 2018. Personalized education to increase interest. *Curr. Dir. Psychol. Sci.* 27:449–54

Ridenour TA. 2019. Precision strategies as a timely and unifying framework for ongoing prevention science advances. *Prev. Sci.* 20:110–14

Ridenour TA, Pineo TZ, Molina MMM, Lich KH. 2013. Toward rigorous idiographic research in prevention science: comparison between three analytic strategies for testing preventive intervention in very small samples. *Prev. Sci.* 14:267–78

Robins E, Guze SB. 1970. Establishment of diagnostic validity in psychiatric illness: its application to schizophrenia. *Am. J. Psychiatry* 126:983–87

Roche MJ, Pincus AL. 2016. Precision assessment: an individualized and temporally dynamic approach to understanding patients in their daily lives. In *The Wiley Handbook of Personality Assessment*, ed. U Kumar, pp. 192–204. New York: Wiley

Roche MJ, Pincus AL, Rebar AL, Conroy DE, Ram N. 2014. Enriching psychological assessment using a person-specific analysis of interpersonal processes in daily life. *Assessment* 21:515–28

Rodgers J, Herrema R, Honey E, Freeston M. 2018. Towards a treatment for intolerance of uncertainty for autistic adults: a single case experimental design study. *J. Autism Dev. Disord.* 48:2832–45

Rosmalen JG, Wenting AM, Roest AM, de Jonge P, Bos EH. 2012. Revealing causal heterogeneity using time series analysis of ambulatory assessments: application to the association between depression and physical activity after myocardial infarction. *Psychosom. Med.* 74:377–86

Rubel JA, Fisher AJ, Husen K, Lutz W. 2018. Translating person-specific network models into personalized treatments: development and demonstration of the dynamic assessment treatment algorithm for individual networks (DATA-IN). *Psychother. Psychosom.* 87:249–51

Shapiro MB. 1961. A method of measuring psychological changes specific to the individual psychiatric patient. *Br. J. Med. Psychol.* 34:151–55

Shiffman S, Stone AA, Hufford MR. 2008. Ecological momentary assessment. *Annu. Rev. Clin. Psychol.* 4:1–32

Skinner BF. 1966. Operant behavior. In *Operant Behavior: Areas of Research and Application*, ed. WK Honig, pp. 12–32. New York: Appleton-Century-Crofts

Smith JD. 2012. Single-case experimental designs: a systematic review of published research and current standards. *Psychol. Methods* 17:510–50

Smith JD, Eichler WC, Norman KR, Smith SR. 2015. The effectiveness of collaborative/therapeutic assessment for psychotherapy consultation: a pragmatic replicated single-case study. *J. Personal. Assess.* 97:261–70

Snippe E, Bos EH, Ploeg KM, Sanderman R, Fleer J, Schroevers MJ. 2015. Time-series analysis of daily changes in mindfulness, repetitive thinking, and depressive symptoms during mindfulness-based treatment. *Mindfulness* 6:1053–62

Stavrakakis N, Booij SH, Roest AM, de Jonge P, Oldehinkel AJ, Bos EH. 2015. Temporal dynamics of physical activity and affect in depressed and nondepressed individuals. *Health Psychol.* 34:1268–77

Tomko R, Solhan M, Carpenter R, Brown W, Jahng S, Wood P, Trull TJ. 2014. Measuring impulsivity in daily life: the momentary impulsivity scale. *Psychol. Assess.* 26:339–49

Toonen RB, Wardenaar KJ, Booij SH, Bos EH, de Jonge P. 2016a. Using local linear models to capture dynamic interactions between cortisol and negative affect. *J. Pers.-Oriented Res.* 2:142–54

Toonen RB, Wardenaar KJ, van Ockenburg SL, Bos EH, de Jonge P. 2016b. Using state space methods to reveal dynamical associations between cortisol and depression. *Nonlinear Dyn. Psychol. Life Sci.* 20:1–21

Trull TJ, Ebner-Priemer U. 2013. Ambulatory assessment. *Annu. Rev. Clin. Psychol.* 9:151–76

van de Leemput IA, Wichers M, Cramer AO, Borsboom D, Tuerlinckx F, et al. 2014. Critical slowing down as early warning for the onset and termination of depression. *PNAS* 111:87–92

van der Krieke L, Blaauw FJ, Emerencia AC, Schenk HM, Slaets JP, et al. 2016. Temporal dynamics of health and well-being: a crowdsourcing approach to momentary assessments and automated generation of personalized feedback. *Psychosom. Med.* 79:213–23

van der Krieke L, Emerencia AC, Bos EH, Rosmalen JG, Riese H, et al. 2015. Ecological momentary assessments and automated time series analysis to promote tailored health care: a proof-of-principle study. *JMIR Res. Protoc.* 4:e100

van der Schans J, Cao Q, Bos EH, Rours I, Hoekstra PJ, et al. 2020. The temporal order of fluctuations in atopic disease symptoms and attention-deficit/hyperactivity disorder symptoms. *Eur. Child Adolesc. Psychiatry* 29:137–44

van Os J, Delespaul P, Wigman J, Myin-Germeys I, Wichers M. 2013a. Beyond DSM and ICD: introducing "precision diagnosis" for psychiatry using momentary assessment technology. *World Psychiatry* 12:113–17

van Os J, Delespaul P, Wigman J, Myin-Germeys I, Wichers M. 2013b. Psychiatry beyond labels: introducing contextual precision diagnosis across stages of psychopathology. *Psychol. Med.* 43:1563–67

van Roekel E, Vrijen C, Heininga VE, Masselink M, Bos EH, Oldehinkel AJ. 2017. An exploratory randomized controlled trial of personalized lifestyle advice and tandem skydives as a means to reduce anhedonia. *Behav. Ther.* 48:76–96

Voelkle MC, Brose A, Schmiedek F, Lindenberger U. 2014. Toward a unified framework for the study of between-person and within-person structures: building a bridge between two research paradigms. *Multivar. Behav. Res.* 49:193–213

Wang W, Harari GM, Wang R, Müller SR, Mirjafari S, et al. 2018. Sensing behavioral change over time: using within-person variability features from mobile sensing to predict personality traits. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.* 2:141

Wichers M. 2014. The dynamic nature of depression: a new micro-level perspective of mental disorder that meets current challenges. *Psychol. Med.* 44:1349–60

Wichers M, Schreuder MJ, Goekoop R, Groen RN. 2018. Can we predict the direction of sudden shifts in symptoms? Transdiagnostic implications from a complex systems perspective on psychopathology. *Psychol. Med.* 49:380–87

Wigman JT, van Os J, Thiery E, Derom C, Collip D, et al. 2013. Psychiatric diagnosis revisited: towards a system of staging and profiling combining nomothetic and idiographic parameters of momentary mental states. *PLOS ONE* 8:e59559

Wood P, Brown D. 1994. The study of intraindividual differences by means of dynamic factor models: rationale, implementation, and interpretation. *Psychol. Bull.* 116:166–86

Woods WC, Arizmendi C, Gates KM, Stepp SD, Pilkonis PA, Wright AGC. 2020. Personalized models of psychopathology as contextualized dynamic processes: an example from individuals with borderline personality disorder. *J. Consult. Clin. Psychol.* 88:240–54

Wright AGC. 2011. Quantitative and qualitative distinctions in personality disorder. *J. Personal. Assess.* 93:370–79

Wright AGC, Beltz AM, Gates KM, Molenaar PCM, Simms LJ. 2015. Examining the dynamic structure of daily internalizing and externalizing behavior and multiple levels of analysis. *Front. Psychol.* 6:1914

Wright AGC, Gates KM, Arizmendi C, Lane ST, Woods WC, Edershile EA. 2019. Focusing personality assessment on the person: modeling general, shared, and person specific processes in personality and psychopathology. *Psychol. Assess.* 32:502–15

Wright AGC, Hallquist MN, Stepp SD, Scott LN, Beeney JE, et al. 2016. Modeling heterogeneity in momentary interpersonal and affective dynamic processes in borderline personality disorder. *Assessment* 23:484–95

Wright AGC, Simms LJ. 2016. Stability and fluctuation of personality disorder features in daily life. *J. Abnorm. Psychol.* 125:641–56

Wright AGC, Zimmermann J. 2019. Applied ambulatory assessment: integrating idiographic and nomothetic principles of measurement. *Psychol. Assess.* 31:1467–80

Yang X, Ram N, Gest SD, Lydon-Staley DM, Conroy DE, et al. 2018. Socioemotional dynamics of emotion regulation and depressive symptoms: a person-specific network approach. *Innov. Aging* 2:15–16

Yarkoni T, Westfall J. 2017. Choosing prediction over explanation in psychology: lessons from machine learning. *Perspect. Psychol. Sci.* 12:1100–22