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How can process-based researchers bridge the gap between individuals and groups? Discover the dynamic p-technique[☆]

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ABSTRACT

Behavioral researchers are concluding that conventional group-based analyses often mask meaningful individual differences and do not necessarily map onto the change processes within the lives of individual humans. Hayes et al. (2018) have called for a renewed focus on idiographic research, but with methods capable of nuanced multivariate insights and capable of scaling to nomothetic generalizations. To that end, we present a statistical technique we believe may be useful for the task: the dynamic p-technique. The dynamic p-technique can accommodate multivariate longitudinal data and may be used to conduct single-subject and group-level analyses. After introducing the dynamic p-technique, we provide several examples of how it may be used in practice by presenting the step-by-step analyses of single-subject daily-diary dataset wherein we examined the day-to-day associations between ADHD difficulties and psychotropic medication. Although it has been underutilized by behavioral researchers, we believe p-technique analyses are particularly well-suited to model personal dynamics with nuance and within context and allow researchers to inductively build from idiographic patterns to nomothetic trends. For a fine-grain walk-through of the analyses presented, including the data and statistical code, link to our supplemental materialshttps://osf.io/cbyj3/

1. Introduction

At the dawn of the era of big data (Harlow & Oswald, 2016), it may seem counterintuitive to suggest behavioral researchers conduct more single-case analyses. However, there is a growing concern across disciplines that group-level analyses can lead to distorted conclusions of person-level processes. Within developmental psychology, “person-centered” approaches have become popular for understanding human development as “holistic, highly interactional, and individualized processes” (Sterba & Bauer, 2010a, p. 239). Very recently, functional MRI (fMRI) researchers have shown that within-person variability in functional connectomes is such that “the global network topology of individual-specific functional connectomes fundamentally differs from the network topology of group-average data” (Gordon et al., 2017, p. 802), leading them to conclude that “individuals must be characterized to understand the prevalence of brain network variants in the general population” (p. 804). As we will see, these conclusions mirror developments within psychometrics, as well (e.g., Asparouhov, Hamaker, & Muthén, 2017; Molenaar, 2004).

In a recent series of clinically-oriented work, Hayes and Hofmann (e.g., Hayes & Hofmann, 2018; Hayes et al., 2018, Hofmann & Hayes, 2019) have argued researchers should adopt a more process-oriented approach for studying and intervening upon human suffering. As a part of their vision, they called upon researchers to place a greater emphasis on context, not only in the form of moderation analyses, but with a renewed attention to ideographic or person-centered methods. For example, Hayes et al. (2018) asserted.

Individual human lives are contextual and longitudinal, as are the change processes that alter these life trajectories. From a process-based point of view, practitioners need coherent and broadly applicable models of change processes that are relevant for the individual in context, that provide increased treatment utility and intervention guidance, and that simplify human complexity. The most popular methodological and analytic tools in use in intervention science are not fully adequate to that task, even when they are turned in the direction of change processes. (p. 3).

Later they clarified that one of the shortcomings in clinical research has been the overemphasis of nomothetic processes, or group trends, to the neglect of careful person-centered analysis. “In order to understand why and how changes happen in an individual, we need to study the

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processes of change at the level of the individual, and then to gather nomothetic summaries based on collections of such patterns" (p. 4). While calls for idiographic (i.e., person-centered) analysis are familiar to those from fields such as behavior analysis (e.g., Sidman, 1952; Skinner, 1956), part of what distinguishes these newer calls is their attention to multivariate analyses (e.g., mediation and moderation), which are poorly-suited for conventional behavior analytic methods, such as the visual analysis of bivariate graphs. Further, if we are to "gather nomothetic summaries based on collections" of idiographic data, we should prefer analytic frameworks capable of seamlessly scaling from single-case to large-group data. Ranging from the time series designs typical in behavior analysis (Smith, 2012) to the intensive assessment periods called for in Gordon et al.'s (2017) idiographic fMRI paradigm, person-centered analyses require longitudinal data. Accordingly, Hayes et al. (2018) called upon researchers to adopt research designs "with far more frequent assessment[s] of change processes in order to increase the intensity of the analytic focus at the level of the individual" (p. 5). Such data sets containing many measurement occasions are often termed intensive longitudinal data (Bolger & Laurenceau, 2013). In the era of big data, developments in and the widespread adoption of mobile technologies are making it easier and less expensive to collect intensive longitudinal data (Miller, 2012; Salganik, 2017). A major challenge is how researchers might effectively analyze such data in a way that emphasizes idiographic processes and still allows researchers to connect those processes to nomothetic generalizations. As we will see, many conventional methods are not up to the task.

In their keynote article on matching person-oriented methods with theory, Sterba and Bauer (2010a) identified several key person-oriented principles, such as individual specificity, complex multivariate interactions, differences across personal developmental processes, and contextualism/holism. They then compared an array of modern statistical paradigms on their ability to model data along those principles. Most popular statistical paradigms were found wanting. For example, while latent growth curve models allow for individual differences in terms of intercepts and slopes—highlighting individual specificity—, individual differences (i.e., random effects) are modeled as minor deviations from the group norms (i.e., population parameters). In addition, these methods restrict the models of participants to the same functional form (e.g., linear, quadratic). Other methods such as latent class growth curve models and growth mixture models allow researchers to detect subgroups, yet the fundamental units of those analyses remain subpopulations (see also Wright & Hallquist, 2014), rather than focusing on person-level processes. Of those paradigms and the others Sterba and Bauer considered, the only methods capable of modeling complex multivariate idiographic data and of scaling to small and large group analyses were those from the dynamic p-technique family (Sterba & Bauer, 2010a; 2010b; also Molenaar, 2010; 2015).

P-technique methods have been underutilized among applied behavioral researchers. Because of their flexibility to connect multivariable single-case research with nomothetic generalizations, the purpose of this article is to present the dynamic p-technique to the JCBS readership. To this end, the article follows a pedagogical approach wherein we first introduce the dynamic p-technique and a description of what it allows analytically. We then provide an overview of several analyses with the dynamic p-technique on real single-subject data from a young adult diagnosed with ADHD. Lastly, we discuss unique considerations inherent to the dynamic p-technique and potential future applications with the types of data available from mobile technologies. To facilitate our aims, the dataset and computer code used herein, as well as finer-grain instructions, are available online as supplemental materials.

2. Introduction to the dynamic P-Technique

P-technique methods originate from the factor analytic tradition (Cattell, Cattell, & Rhymer, 1947; cf.; Brose & Ram, 2012). Cattell and colleagues' innovation was that data collected from an individual on several related variables across many occasions could be used to conduct a single-subject factor analysis. In this way, behavioral researchers could assess whether factor models estimated from group-level data generalized to individuals (for discussions, see Molenaar, 2004; Molenaar & Campbell, 2009). The initial method was limited in that it did not explicitly model the serial dependencies inherent in time series data. That is, it did not take into account when measurements on one occasion partially depend on the values from the previous occasion (see Little, 2013). Subsequent work (e.g., Molenaar, 1985; Nesselroade & Ford, 1985) generalized Cattell's p-technique with the dynamic p-technique, which explicitly models serial dependencies inherent in single-subject data and better captures their longitudinal nature. Within the literature, variants of the technique go by a number of names, such as dynamic factor analysis, direct autoregressive factor score specification, and dynamic structural equation modeling (Asparouhov et al., 2017). Across these methods, the common thread is their emphasis on multivariate idiographic processes within a structural equation modeling (SEM) framework.

For idiographic exploratory factor analyses (EFA), behavioral researchers have used the p-technique in areas such as big-five personality research (Borkenau & Ostendorf, 1998) and the therapeutic alliance (Russell, Jones, & Miller, 2007). With the dynamic p-technique, researchers examined topics such as the day-to-day symptom profiles and dynamics of adults diagnosed with generalized anxiety disorder (GAD; Fisher, 2015) and the day-to-day relations among negative affect, craving, and tobacco use (Zheng, Wiebe, Cleveland, Molenaar, & Harris, 2013). Note that the dynamic p-technique framework allows researchers to focus on either idiographic factor structures (i.e., measurement models) or the relations among variables within individuals (i.e., structural models; Little, 2013). In addition to single-subject models and models of individual dyads, researchers can use the dynamic p-technique to inductively perform group analyses with procedures similar to multigroup factor analysis (Little, 2013) and multilevel modeling (Asparouhov et al., 2017; Song & Zhang, 2014). Also, used as a general statistical method, dynamic p-technique models may include observed variables as well as latent variables (Hamaker, Nesselroade, & Molenaar, 2007; Nelson, Aylward, & Rausch, 2011). Thus, the framework allows for analyses across the full spectrum of single-case data, small-*n* data, and large-scale group data, a unique strength relative to other statistical frameworks (Molenaar, 2010; Sterba & Bauer, 2010a; 2010b).

3. Example dataset: Daily ADHD ratings

3.1. Participant and procedure

To show how one might use the dynamic p-technique, we present several analyses of single-subject daily diary dataset. "Lindsey" was a participant in the first author's dissertation study (Kurz, 2018), for which she provided informed consent. She was a White female in her early twenties who was registered at her university as having been diagnosed with ADHD. She was enrolled in a semester-long introductory course on mindfulness meditation, during which she recorded a variety of variables in her smartphone in a daily diary fashion (Bolger & Laurenceau, 2013). For the purpose of this article, we will focus on the date, her self-reported ADHD symptoms, and psychotropic medication consumption.

3.2. Measures

To assess day-to-day attention- and hyperactivity/impulsivity-related difficulties, Lindsey completed a modified past-day Adult ADHD Self-Report Scale (ASRS; Kessler et al., 2005). The ASRS is an 18-item questionnaire designed to map directly on the 18 Criterion A items for

ADHD in the DSM (APA, 2013). Our past-day version retained Kessler et al.'s 5-point Likert-type format, though we slightly amended the anchors to make sense within a daily diary format such that they ranged from 0 (*Not at all*) to 4 (*All day long*). Similar to Joos et al., (2012), we reworded items to better facilitate day-to-day ratings (see supplemental material). For example, "How often are you distracted by activity or noise around you?" was reworded to "Were you distracted by activities or noises around you?". To reduce participant burden, Lindsey completed a subset of the original 18 items. At the beginning of the semester, she indicated items 3, 8, 10, 13, 14, 16 and 17 were most meaningful to her; these were the items used throughout the study.

Along with the other participants in the study, we created a custom online survey for Lindsey, onto which she logged once a day to record her ASRS ratings for that day. In this study, participants were eligible regardless of whether they took psychotropic medication for ADHD. Lindsey did have a prescription which she reported she consumed as needed. To track her consumption, we included the question "Did you take ADHD medication?" in her online questionnaire. See Kurz (2018) for further details. This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

3.3. Statistical analysis

Of the recent introductions to and tutorials on the dynamic p-technique (e.g., Nelson et al., 2011; Ram, Brose, & Molenaar, 2013; Hamaker, Asparouhov, Brose, Schmiedek & Muthén, 2018), we believe the method outlined in Little's (2013) text is the most approachable for non-statistician behavioral researchers. Thus, the approach described herein is based primarily on Little's text. Longitudinal structural equation models (SEMs), such as those estimated with the dynamic p-technique, can become very complex. The method recommended herein, therefore, starts with relatively simple models and sequentially builds to more complex ones. More specifically, we will (a) estimate the basic measurement model for Lindsey's ASRS ratings, (b) estimate the autoregressive structure for those ASRS ratings, (c) estimate a model including the day-to-day relations between psychotropic medication consumption and ASRS ratings, and (d) estimate a mediation model in which medication consumption mediates the day-to-day autoregressive relation of the Lindsey's ASRS ratings. In order to make the approach outlined in this paper widely accessible, we analyzed the data in the free and open source R computing environment (R Core Team, 2018), with particular use of the lavaan package (Rosseel, 2012). Interested readers can find a detailed description of our analysis, including statistical code at https://osf.io/cbyj3/.

4. Data analyses and results

4.1. Preliminary analyses

As with typical group-level analysis, researchers should thoroughly examine the distributional characteristics of their data and look for missing values prior to a dynamic p-technique analysis. This can be done with both visual inspection and typical descriptive statistics (see the supplemental materials). Contemporary SEM software packages offer a variety of estimators capable of handling data from numerous distributional families as well as missing data. In this paper, we used the full information nonnormal robust maximum likelihood estimator (MLR; Yuan & Bentler, 2000; Zhong & Yuan, 2011). Lindsey submitted responses for her ASRS items on 87 occasions (84.5% of the days possible). In the analyses that follow, missing values were handled with the conventional missing at random assumption (see Enders, 2010).

4.2. P-technique factor analysis

As the first step for analyzing Lindsey's ADHD ratings, we examined the factor structure of her ASRS items with p-technique factor analysis as originally proposed by Cattell et al. (1947). For simplicity, we focused on her primary hyperactivity/impulsivity items from the ASRS, items 10, 13, 14, 16, and 17. Based on prior research, we expected a single-factor structure would suffice. The model passed the χ^2 test (6.8, $df = 5$, $N = 87$, $p = .24$), suggesting it was a good description of the data (Brown, 2015; Little, 2013). Yet the standardized item loadings were diverse, with items 13, 14 and 17 loading above 0.4, but items 10 and 16 showing surprisingly low loadings of 0.28 and 0.06, respectively (see Fig. 1). This suggests Lindsey's ADHD-related difficulties assessed by the latter two items occurred somewhat independently of the other three.

A limitation of this initial model is that it ignored the serial dependencies inherent in time series data (Little, 2013). It implicitly presumed the occasion-to-occasion dependencies were equal to zero. In the next section, we estimated a dynamic p-technique CFA to explicitly model the dependencies in Lindsey' data.

4.3. Dynamic p-technique factor analysis

The dynamic p-technique framework is flexible and allows many ways to handle the serial dependencies among the Lindsey's ASRS ratings. Here we model a simple first-order autoregressive structure (AR_1) by estimating two latent variables H/I_{today} and $H/I_{tomorrow}$, setting the former to predict the later (see Fig. 2). For examples beyond the simple AR_1 model, see Little's (2013) text, the chapter by Lee and Little (2012), and Asparouhov et al. (2017) for a more technical discussion. Setting up such models requires a lagged data file, which we detail in our supplemental material (see also Little, 2013; Nelson et al., 2011). Also following Little's text, we included residual correlations for the same items across time lags (e.g., item 10 in H/I_{today} has a residual correlation with item 10 in $H/I_{tomorrow}$).

This model assessed two research questions: 1) what is the autoregressive factor structure for Lindsey's daily-diary ASRS items? and 2) How stable were her ratings from day to day? The fit statistics indicated the model was a very good fit for the data: χ^2 ($df = 42$, $N = 100$) = 31.4, $p = .88$. The factor loadings were similar to those in the p-technique factor model, above. However, the autoregressive parameter, .51 95% CI [0.28, 0.74], added fresh perspective. The estimate is in a correlation metric and suggests Lindsey's ASRS ratings were fairly stable from day to day, an insight missing from our first model. Within the clinical intensive longitudinal literature, autoregressive parameters are sometimes colorfully termed inertia (see Jongerling, Laurenceau, & Hamaker, 2015).

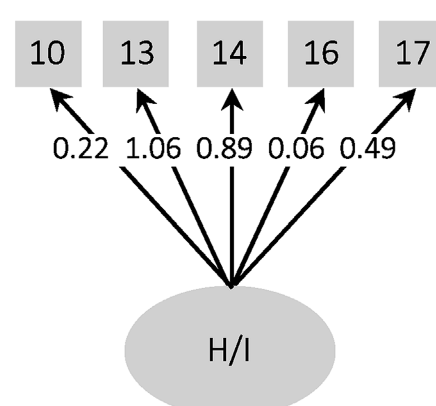

Fig. 1. The measurement model for the p-technique CFA of Lindsey's ASRS data. For visual simplicity, we have omitted the mean structure and the residual variances from the figure. The boxes are labeled by ASRS item number and H/I = hyperactivity/impulsivity. The loadings are in the standardized metric.

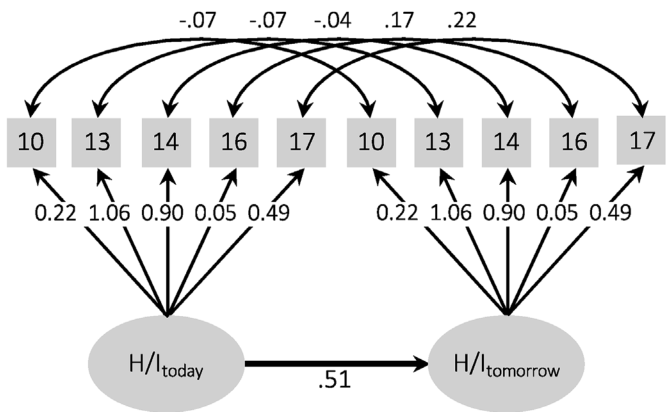

Fig. 2. The dynamic p-technique CFA of Lindsey's ASRS data. The curved arrows depict the residual correlations and the thick dark arrow depicts the autoregressive parameter.

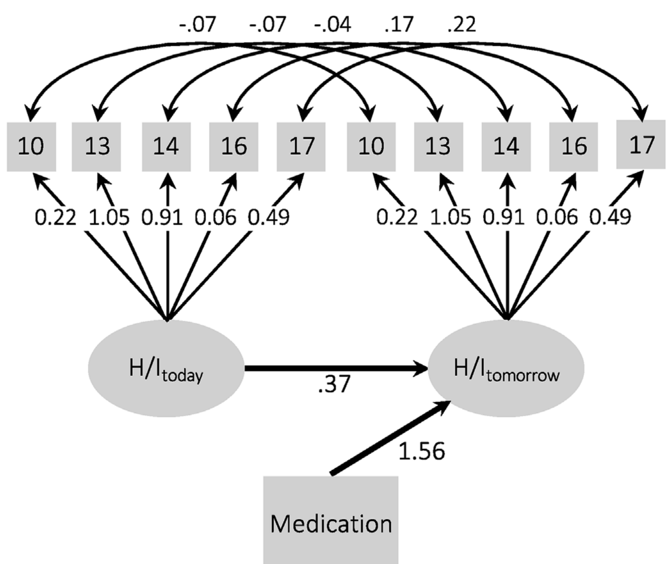

Fig. 3. Dynamic p-technique SEM predicting Lindsey's ASRS ratings from medication consumption.

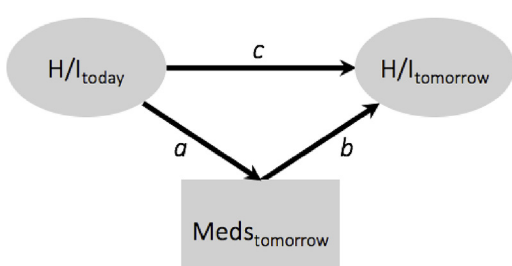

Fig. 4. The basic mediation model as applied to Lindsey's data.

4.4. Dynamic p-technique SEM

Though psychometric questions have intrinsic merit, a strength of the SEM framework is the ability it affords researchers to enter covariates into the models. Here we add to the model a dummy variable depicting whether Lindsey consumed her prescribed ADHD medication on a given day. As we continued to use the dynamic framework, the effect of the medication on same-day ASRS ratings had the prior day's ASRS ratings as a control via the autoregressive parameter. The resulting fit statistics suggested the model was a good fit for the data: χ^2 ($df = 51$, $N = 87$) $= 51.92$, $p = .44$. The primary coefficient was $\text{Medication}_{\text{tomorrow}}$ predicting $\text{H/I}_{\text{tomorrow}}$ (see Fig. 3). Because this coefficient was of a binary variable predicting a standardized variable, the resulting value of 1.58 [1.19, 1.97] was in a Cohen's *d*-type metric (Brown, 2015). That is, Lindsey's ASRS ratings were substantially higher on days she took her medications.

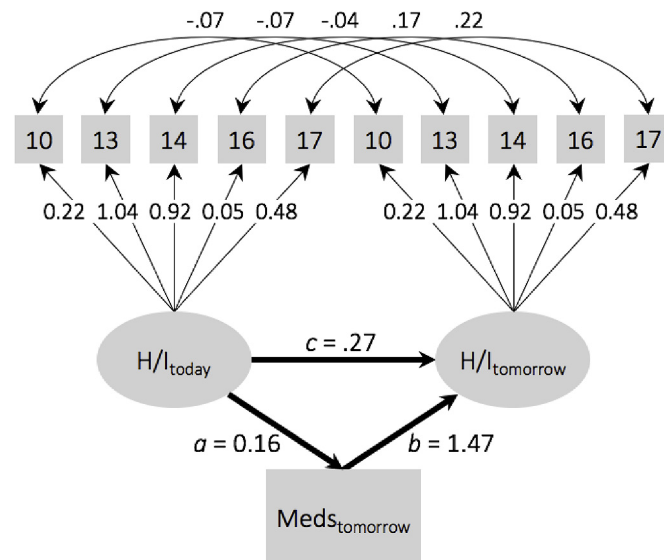

Fig. 5. One version of a dynamic p-technique longitudinal mediation analysis. The indirect effect *ab*, 0.24 [0.14, 0.45], suggested psychotropic medication mediated the autoregressive relationship of Lindsey's daily ASRS ratings.

This finding could be interpreted in multiple ways, the simplest of which being Lindsey tended to take her medication on days she felt she needed it. To this end, a closer look at her data revealed that her medication consumption was in fact highly correlated with school days.

Another possible explanation for this finding is that she tended to experience greater ADHD-related difficulties on school days, which also happened to coincide with medication consumption. A more structured experiment would be required to clarify the causal relationships, which could also be modeled with dynamic p-technique SEMs. For our purposes, the take home point is the dynamic p-technique framework allowed us to compute a single-subject effect size in a metric commonly used in group-based analyses, something needed to connect the single-case and group-based literature (Shadish, 2014).

4.5. Dynamic p-technique mediation

Within the p-technique framework, analysts can examine complex relationships among variables. To demonstrate, we present a longitudinal mediation model in which we assessed whether the effects of Lindsey's ASRS today on her ASRS tomorrow was mediated by taking her medication tomorrow morning. In common terms from the mediation literature (see Hayes, 2017), the effect of $\text{H/I}_{\text{today}}$ on $\text{Medication}_{\text{tomorrow}}$ was the *a* pathway, the effects of $\text{Medication}_{\text{tomorrow}}$ on $\text{H/I}_{\text{tomorrow}}$ was the *b* pathway, and their interaction was the indirect effect, the *ab* pathway (see Fig. 4). The autoregressive parameter served as the *c* pathway, the direct effect.

The resulting fit statistics suggested the model fit the data well: χ^2 ($df = 50$, $N = 100$) $= 46.77$, $p = .60$. The model is depicted in Fig. 5. Following common practices within the contemporary mediation literature, we included 95% bootstrap confidence intervals along with the coefficient for the *ab* pathway: 0.24, [0.14, 0.48]. These estimate suggests the day-to-day autoregressive parameter for Lindsey's ASRS ratings (i.e., her ADHD inertia) was mediated by her medication consumption. Of note, this analysis was not among those proposed in the original study and is only presented here in order to give a sense of the possibilities within this analytic framework.

5. Discussion

The primary goal of this manuscript was to introduce JCBS readers to the dynamic p-technique. We believe the technique is uniquely well suited to respond to Hayes et al.'s (2018) call for increased multivariate idiographic research. The dynamic p-technique was showcased by a series of analyses using daily-diary data from Lindsey, a college student with a prior diagnosis of ADHD.

Our first analysis used p-technique CFA to discover Lidsey's difficulties fidgeting (ASRS item 10) or talking over others (item 16), were fairly independent of her difficulties relaxing, feeling as if driven by a motor, or waiting her turn in activities (items 13, 14, and 17, respectively). This is consistent with a general trend across studies employing p-technique methods: Group-based findings often translate poorly to individuals (Fisher, Medaglia, & Jeronimus, 2018). For example, with 101 German young adults across 100 days, Brose, Voelke, Lövdén, Lindenberger, and Schmiedek (2015) found the idiographic factor structures for positive and negative affect differed across individuals and differed from the cross-sectional factor structure. Fisher (2015) found similar differences in anxiety profiles and their day-to-day dynamics in 10 Americans diagnosed with Generalized Anxiety Disorder. Commenting on this, Hayes et al. (2018) asserted this pattern of findings revealed "important differences in symptom relations resulting from an idiographic approach to assessment," and further, that these differences have meaningful implications for personalizing interventions, "as targeting symptom clusters that drive changes in other symptoms for an individual could be beneficial" (p. 7). In Lindsey's case, it appears different strategies might be necessary to target her tendency to talk over others than for targeting her difficulties relaxing.

In the second model, we used the dynamic p-technique approach to further explore the day-to-day stability of Lindsey's ratings. With the model's autoregressive parameter (i.e., inertia) we discovered her ratings were fairly stable from day to day, exhibiting both trait and state like qualities. The notion of inertia is new within the clinical literature and may be of interest beyond simple psychometrics. For example, Kuppens et al. (2012) discovered adolescents with greater emotional inertia were at greater risk of a major depressive episode two years later. Contextual behavioral scientists might consider inertia as a new way to measure psychological flexibility. For example, adopting intensive longitudinal designs and the dynamic p-technique would allow researchers to assess whether behavioral interventions decreased emotional inertia or the inertia of maladaptive coping strategies.

In the third model, we added a covariate which provided single-subject effect size for the effect of Lindsey's medication on her ASRS ratings. A particular strength of the dynamic p-technique is its ability to yield single-subject effect sizes in metrics familiar to nomothetic researchers, such as the Cohen's *d*, something needed within the single-case literature (Shadish, 2014). Such single-case effect sizes should further aid researchers and theorists wishing to synthesize the idiographic and nomothetic literature in reviews and meta-analyses.

For the final model, we showcased an example of single-subject mediation. Grice, Cohn, Ramsey, and Chaney (2015) demonstrated that results from mediation analyses based on group-level data do not necessarily apply to the general population, nor even to the individuals from whose data the group-level analyses were conducted (cf. Fisher et al., 2018). However, the dynamic p-technique framework allows researchers to examine mediation at the level within which it occurs, within the lives of single participants. In this way, p-technique analyses may be an invaluable tool for researchers to heed the calls within the contextual-behavioral (e.g., Hayes, Barnes-Holmes, & Wilson, 2012) and process-based literature (Hayes & Hofmann, 2018; Hayes et al., 2018, Hofmann & Hayes, 2019) to increase efforts to examine mediation, moderation and other complex models of person-centered behavioral processes.

To highlight the strengths of the p-technique framework for multivariate idiographic analyses, our tutorial focused on the data of a single participant. However, this framework can seamlessly scale. A minor extension would to be use the technique in couples (e.g., Ferrer & Nesselroade, 2003) or other dyads, such as therapists and their clients. With small numbers of participants, one may use methods from multigroup factor analysis to assess whether either factor structures or relations among variables are identical across individuals (e.g., Kurz, 2018; Little, 2013). Researchers may also set p-technique analyses within a multilevel framework to partially pool across many participants in large-scale studies (e.g., Asparouhov et al., 2017; Song & Zhang, 2014). Finally, as a general statistical approach nested within the regression framework, these model types can accommodate missing data, nonnormal distributions and models with or without latent variables, all of which are common challenges in the kinds of data recorded by contemporary methods and technologies.

5.1. Limitations

The dynamic p-technique has several limitations. From a methodological perspective, the technique typically presumes the analyzed processes are stable. Using the dynamic p-technique to examine data collected during a period when the relations among the variables were in flux (e.g., within the context of a clinical intervention) may result in biased models (Ram et al., 2013). Though methodologists have proposed ways to relax the traditional stability restriction (e.g., Chow, Zu, Shifren, & Zhang, 2011; Molenaar, 2010), further work is needed. As power for group-level analyses increases with larger sample sizes, power for dynamic p-technique analyses increases with each successive measurement occasion. Thus, even simple models containing a single brief questionnaire may require upwards of 50 measurement occasions for reasonably powered parameter estimates (Little, 2013). However, the need for numerous measurement occasions will be less of a concern as researchers collect data using smart technology. From a practical standpoint, the dynamic p-technique requires fluency with statistical methods beyond those provided in many psychology graduate programs. At a minimum, it requires fluency with path analysis, and proficiency is greatly facilitated by familiarity with factor analysis and longitudinal SEM (for excellent introductions, see Brown, 2015; Little, 2013). Newer variants also require fluency with Bayesian statistics and multilevel modeling (Asparouhov et al., 2017).

6. Conclusion

Across a variety of disciplines, behavioral researchers are rediscovering the insights long held among behavior analysis: Group-based analyses can mask theoretically meaningful individual differences and simple moderation and subgroup analyses are insufficient to the task. In order to better understand and intervene on behavior as it unfolds in the lives of individuals, researchers require rich contextual frameworks capable of scaling seamlessly from idiographic patterns to nomothetic generalizations. Within statistics, the approaches from within the p-technique family appear uniquely well-suited to examine complex multivariate dynamics in individuals, within small groups, and in large-scale studies, too. We believe behavioral researchers will find these methods useful for better integrating idiographic and nomothetic approaches and more effectively understanding and improving upon the lives of those they serve.

Disclosure statement

The views expressed in this article are those of the authors and do not reflect the official policy or position of the Department of Veterans Affairs.

Conflicts of interest

The authors have no conflicts of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jcbs.2019.07.001.

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