Foundations of Idiographic Methods in Psychology and Applications for Psychotherapy

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Abstract

Researchers have long called for greater recognition and use of longitudinal, individual-level research in the study of psychopathology and psychotherapy. Much of our current research attempts to indirectly investigate individual-level, or idiographic, psychological processes via group-based, or nomothetic, designs. However, results from nomothetic research do not necessarily translate to the individual-level. In this review, we discuss how idiographic analyses can be integrated into psychotherapy and psychotherapy research. We examine and review key statistical methods for conducting idiographic analyses. These methods include factor-based and vector autoregressive approaches using longitudinal data. The theoretical framework behind each approach is reviewed and critically evaluated. Empirical examples of each approach are discussed, with the aim of helping interested readers consider how they may use idiographic methods to analyze longitudinal data and psychological processes. Finally, we conclude by citing key limitations of the idiographic approach, calling for greater development of these analyses to ease their successful integration into clinical settings.

Keywords

Idiographic, Individual-level, Methodology, Psychopathology, Psychotherapy

Foundations for Idiographic Methods in Psychology and Applications for Psychotherapy

Many researchers have argued that the field of psychology is inherently focused on the study of the individual – an individual's behavior, his or her cognitive processes, and his or her personality (Barlow & Nock, 2009; Molenaar, 2004; Molenaar, Rovine, & Corneal, 1999). However, to date, most clinical psychological research has focused almost exclusively on the study of the group – groups of individuals with a certain psychiatric disorder or a specific behavioral signature (as noted by Barlow & Nock, 2009). Arguably, the predominance of group-level research has been influenced both by the historical preferences of agencies that have funded large-scale clinical trials to evaluate therapies for specific psychiatric disorders (Barlow & Nock, 2009), as well as by practical limitations, such as the availability of suitable statistical methods. Although group-level research remains commonplace, the field of precision medicine is rising and funding agencies have begun to fund grants to personalize interventions for individuals within the aggregate (NIH, 2017).

As reviewed by Hamaker (2012), the psychologist Gordon Allport posited that the purpose of large-scale (i.e., nomothetic) research was to identify general laws of psychology (Allport, 1946). In other words, to identify universal psychological processes, researchers needed to study large groups of individuals. This belief contributed to the notion that group-level statistics could translate to individual-level inferences (Hamaker, 2012). Researchers following this argument may be likely to believe that single-subject research carries little merit, as its findings cannot be generalized to the larger group (because the individual may be atypical compared to the greater population) (cf. Molenaar et al., 1999). Although generalizability to the wider population is inarguably limited in single-subject research, even relatively homogenous groups (e.g., those selected for specific characteristics) are made up of heterogeneous individuals, and thus results from these studies are also inevitably limited in generalizability (Molenaar et al., 1999).

Clinicians and researchers have long advocated for an increased idiographic focus in psychotherapy (Howard, Moras, Brill, Martinovich, & Lutz, 1996). Psychotherapy research within the cognitive-behavioral realm has primarily been conducted using nomothetic, group-level approaches (Barlow & Nock, 2009), although notable exceptions – often from the psychodynamic literature – have used an idiographic approach (Luborsky & Mintz, 1972; Russell, Jones, & Miller, 2007). The relative lack of individual-level research results in a tension for clinician-scientists known as *the therapist's dilemma* – a phrase describing the situation of being trained primarily in nomothetic research methodology, yet being tasked with determining the course of treatment for a single individual (Levine, Sandeen, & Murphy, 1992). Howard and colleagues (1996) argued that, to implement successful psychotherapy, clinicians must consider whether their intervention is successful under three conditions: experimental settings, general practice settings, and in the setting for their *individual patient* (Howard et al., 1996).

Numerous studies have supported the efficacy of empirically-supported therapy in research settings (Chambless et al., 1998). Meta-analyses have also demonstrated the efficacy of therapy in general practice (i.e., non-research) settings (Shadish et al., 1997). Fewer studies have studied the effect of therapy for an individual patient (Howard et al., 1996). Although idiographic methods discussed here have been used for decades to conduct case studies of psychotherapy process (e.g., Russell et al., 2007) and some methods exist for constructing individualized treatment plans (e.g., Cognitive-Behavioral Case Formulation, Persons, 2006), idiographic research has rarely been integrated into treatment or applied settings in a systematic way. The primary limitation with integrating these methods at present centers on the amount of labor involved with collecting data and the complexity of analyzing it.

These limitations may not seem important to overcome if a clinician or researcher assumes that group-level results plausibly inform their practice with individuals. However, the assumption that group-level statistics will elucidate general laws that apply to even a majority of the individuals in the sample reflects a fallacy long-noted by researchers (Brose & Ram, 2012; Hamaker, 2012; Molenaar, 2004). Results from cross-sectional nomothetic research do not account for both between person and within person differences, meaning that group-level research may not describe any one individual within the group (Hamaker, 2012; Lamiell, 1998; Molenaar, 2004). Yet, the use of results from group-level designs to inform knowledge of individual-level processes persists (as described in Borsboom, Mellenbergh, & van Heerden, 2003; Molenaar, 2004).

In this review, we will (1) examine methodologies for studying the individual and modeling intraindividual variability, (2) highlight key empirical studies that use idiographic and related methodology, and (3) discuss potential limitations regarding the integration of idiographic methods into clinical practice. Although we will advocate for the increased use of individual-level designs within psychological research, we firmly believe that both group and individual-level designs have merit and should be used *in conjunction* to provide information about psychological processes at different levels of analysis. Rather than pursuing one level of analysis to the exclusion of the other, we offer that psychologists should carefully consider the aims of their research and conduct analyses at the appropriate level of interest.

Background for Idiographic Methods

Since the 1930's, several methods have been developed to study the individual over time. These analytic techniques are often referred to as idiographic analyses or time-series analyses. Conventional cross-sectional research examines relationships between variables measured on one occasion (Cattell, 1952). In contrast, individual-level time-series analysis examines relationships between variables within one person across many occasions (Cattell, Cattell, & Rhymer, 1947). Time-series methods are used in many fields of research, especially in mathematics and econometrics, and are becoming increasingly prominent in psychological research. It is important to note that these methods can be used to analyze group or individual-level data, as will later be discussed.

First, we should address some ways we focused this paper, as well as the assumptions shared by the techniques we review. We will focus exclusively on linear models for continuous, normally distributed variables, because these models are currently the most accessible to clinicians and researchers. Note that there are many other time series methods for variables that are not normally distributed (e.g., binary variables, cf., Barber & Drton, 2015), and the interested reader will also find that some of the approaches we cover have been extended to such situations. Additionally, the methods discussed in this review assume a multivariate normal distribution (Hamaker, Ceulemans, Grasman, & Tuerlinckx, 2015). The methods all are recommended for use with data that have even spacing between time points to facilitate interpretation of results.[1] As well, it is assumed that missing data are missing at random, although not completely at random (see Hamaker et al., 2015 for more details).

[1] One limitation of discrete time models is that the results can only be assumed to apply to the specific time interval used in the study. For example, results obtained when data are collected every hour versus every three hours may differ, complicating the comparison across studies that use different time intervals. Researchers have been moving more towards statistical implementation to cope with uneven spacing (see Hamaker, Asparouhov, Brose, Schmiedek, & Muthén, 2018) and focus on continuous time instead of specific spacing (c.f., Driver, Oud, & Voelkle, 2017; Oravecz, Tuerlinckx, & Vandekerckhove, 2011; Voelkle, Brose, Schmiedek, & Lindenberger, 2014).

Commonalities. Figure 1 provides an overview of the theories behind the idiographic methods we discuss; we encourage readers to use this figure as a guide. These methods have some commonalities. Nearly all the methods reviewed model lagged and cross-lagged effects. A *lagged effect* is defined as the relationship between the same variable at time t and a previous time, t - 1 (i.e., autocorrelation or autoregression). For example, the amount to which an individual's depressed mood at one time point is predicted by their depressed mood from the previous time point represents a lagged effect. A *cross-lagged effect* is defined as the relationship between one variable at time t and another variable at a previous time, $t - 1$. For example, the amount to which an individual's depressed mood is predicted by the amount of physical activity he or she engaged in at the previous time point represents a cross-lagged effect.

Causality within time-series. The use of lagged effects means that interpretation of time series methods in general depends at least in part on Granger causality theory (Granger, 1969). A relationship between two variables (e.g., variable A and variable B) is said to be *Granger casual* if variable A is a predictor of future values of variable B, after accounting for past values of variable B (Brandt & Williams, 2007). An example of Granger causality is demonstrated in Figure 2. All of the methods we describe, except for P-technique, can be said to model Granger causality, which is generally believed to allow improved causal inference compared to cross-sectional data, but is nevertheless certainly not the strongest grounds for causal inference (cf. a true experiment; see Brandt & Williams, 2007; Granger, 1969).

Differences. Beyond the commonalities described above, the analytic techniques discussed in this review are primarily differentiated by three features: (a) the level of analysis (e.g., multilevel or individual), (b) the structure of variables (e.g., latent variables or observed variables), and (c) how they cope with violations to *ergodicity*. The latter point requires some further explanation.

Ergodicity and psychological processes. For individual-level inferences to be valid when interpreting group-level findings, the process being modeled must be *ergodic* – in other words, the process must behave similarly between groups and individuals (Molenaar & Campbell, 2009; Molenaar, 2004). Ergodic processes meet two conditions: homogeneity and stationarity. The homogeneity condition implies that the psychological process exhibits the same average and variance over time across individuals. The stationarity condition implies that the process does not exhibit systematic changes over time (Molenaar, 2004; Molenaar & Campbell, 2009). We find it plausible that psychological processes violate conditions of ergodicity in at least some common scenarios. For example, the observation that individuals react differently to life events suggests that the homogeneity condition may not hold. All idiographic methods, by definition, attempt to cope with the possibility that ergodicity fails due to lack of homogeneity. However, not all the methods we review attempt to cope with violations of *stationarity*.

Instead, most time-series methods continue to rely on the assumption of stationarity. Stationarity refers to three principles that govern the structure of a normally distributed time series (Bringmann et al., 2016): (1) the means of each item measured, (2) the variance of each item measured, and (3) the covariance between each pair of items measured. In less formal language, these elements refer to levels of variables, how widely these levels fluctuate, and how tightly tied the level of one variable is to the level of another. Regarding (1), the mean of the time-series should not be a function of time: Levels should not go up or down systematically. However, most developmental processes (e.g., pubertal status or height) violate this principle, as the mean level of the developmental process changes systematically with time. Regarding (2), the variance of each item in a series should not be a function of time. Thus, an increase in moodiness, leading to wider variation in affect levels as an individual enters adolescence would violate this principle. Finally, regarding (3), covariances in the model should not change over time: If a person's depression usually tracks their anxiety quite closely, it would violate stationarity if this tracking decreased over time.

Testing for stationarity. Econometricians have developed tests to evaluate whether a time series violates stationarity. These tests evaluate the presence of linear trends (e.g., the Kwiatkowski-Phillips-Schmidt-Shin test; Kwiatkowski, Phillips, Schmidt, & Shin, 1992), or the presence of a non-linear trends (e.g., the Dickey-Fuller Test and Phillips-Perron Test; Dickey & Fuller, 1979; Phillips, 1987; Phillips & Perron, 1988), in the data. Although such tests have been used in select studies reviewed here (e.g., Bringmann et al., 2013; van der Krieke et al., 2015), these tests have limitations that may explain why they are not being routinely used within psychological research. For example, they do not handle missing data well; nor can they model some non-linear trends that violate stationarity (cf. Bringmann et al., 2016).

Resolving stationarity violations. Researchers have often attempted to subtract out a linear trend in order to obtain approximately stationary models (Bringmann, Hamaker, et al., 2016). Although this technique is commonly used, it may lead to faulty assumptions about the structure of the data. For example, although we may assume a linear trend in psychotherapy outcome data (e.g., a steady decline in symptoms), in reality, change may be nonlinear. In instances in which change is non-linear or when autocorrelations violate stationarity, modeling a linear trend would result in incorrect model estimates (Bringmann et al., 2016). Researchers have begun to develop additional methods of testing for and dealing with other forms of non-stationarity in psychological processes, known as time-varying methods (Bringmann et al., 2016). We include such methods in our review. It is worth noting, however, that another potential way to handle problems with stationarity is to model a linear trend rather than subtract one out (c.f., Hamaker & Dolan, 2009), a strategy that can be extended to nonlinear trends if they are already known to exist. However, among the studies reviewed here, detrending the data (i.e., subtracting the trend) before modeling appears to be the more common strategy for addressing violations to stationarity.

Multilevel Methods Using Time Series Data

Having provided some background, we begin our review with multilevel time series methods that have been developed to evaluate both between and within person variability. In other words, results from this type of analysis can provide information about fixed (e.g., group-level) as well as random (e.g., individual-level) effects (see Bringmann et al., 2013; Jongerling, 2016; Suls, Green, & Hillis, 1998). Notably, in multilevel models, within-person variability is pooled across individuals, rather than person-specific (Bringmann et al., 2013). Therefore, some researchers would question the inclusion of multilevel models in this review at all: These models only handle individuals as departures from group-level means. There may be instances in which such a model is completely appropriate, but multilevel models in isolation cannot provide evidence as to whether this is the case or not. For example, multilevel models must make an assumption about how the group's parameters are distributed, and this assumption might be incorrect. If the assumption is incorrect, the individual parameter estimates will also be incorrect. In the absence of prior information regarding the distributions, consulting fully idiographic methods in combination with a multilevel model would be necessary to determine whether the multilevel model was reasonably appropriate.

One reason to review such models despite this shortcoming is that multilevel models are often more tractable than the truly idiographic $N = 1$ version of a given model. That is, in our experience, the relevant multilevel model often requires fewer timepoints and runs into fewer convergence problems than an $N = 1$ model with any given individual from the data set (Schultzberg & Muthén, 2018). In other words, multilevel techniques may not be truly idiographic, but they are a step in that direction, and sometimes the only step that can be taken with a given dataset. Thus, it seems useful to review multilevel techniques as an additional strategy for estimating individual-level effects, in conjunction with our review of purely idiographic methods.

The studies reviewed here have primarily used multilevel vector autoregression (VAR), which is a method that measures lagged and cross-lagged relationships among vectors (i.e., observed variables) at the between and within-person level. Additionally, one study we reviewed used multilevel structural equation modeling and multilevel dynamic factor modeling, whereas another used multilevel dynamic structural equation modeling (DSEM). DSEM, unlike multilevel VAR, uses a Bayesian estimation method. Interested readers may wish to examine related work for additional details (Lodewyckx, Tuerlinckx, Kuppens, Allen, & Sheeber, 2011; Schuurman, Ferrer, & Hamaker, 2016; Song & Ferrer, 2012). Other than estimation methods, these multi-level methods primarily differ on the assumptions regarding the structure of the variables (i.e., observed versus latent).

One of the first studies to utilize multilevel VAR was conducted by researchers who examined positive and negative emotions across an average time frame of 1.5 hours, across several days. Researchers constructed a group network modeling the relationships among positive and negative emotions across time and examined whether this group network differed based on personality traits. They found that higher levels of neuroticism predicted denser or more tightly connected negative emotion networks, suggesting that neuroticism may be defined by a specific set of (co-occurring) negative emotions. These denser networks also exhibited stronger autoregressive relationships, which indicates that these negative emotions may be more stable across time for individuals higher in neuroticism (Bringmann, Pe, et al., 2016). This study provides some evidence of the interaction between trait personality traits (i.e., neuroticism) and the dynamics of state affect (i.e., negative emotions) over time.

Another study that used a multilevel autoregressive model measured daily positive affect over several weeks (Jongerling, Laurenceau, & Hamaker, 2015). Using a simplified multilevel VAR model, they demonstrated that, for the group, there was a statistically significant autoregressive effect, such that positive affect on one day was predicted by positive affect the day before. Again, this provides evidence of the stability of affect over time. Similarly, there was statistically significant variance in the average positive affect over time and statistically significant between-person variance. That is, individuals differed in their average levels of positive affect, as well as in the variability of positive affect over time (Jongerling et al., 2015). Both studies highlight intraindividual variability within the group context and suggest potential for further analysis using idiographic methods to examine the nature and extent to which individuals differ from the group.

Similarly, a study by Hamaker and colleagues (2018) utilized multilevel DSEM to model to data from a longitudinal study of affect (the COGITO study) for both older and younger adults. Results from a fixed-effects analysis (i.e., between-person effects) suggested that affect valence had more of an autoregressive, rather than cross-lagged effect over time, although the strength of this effect was moderated by age (Hamaker et al., 2018). That is, individuals on the whole who were higher in negative affect were more likely to have more carryover of their negative affect from one time point to the next. Furthermore, those individuals who were higher in positive affect were more resistant to spillover of negative affect into positive affect.

A second model examined the random-effects (i.e., within-person effects). Results from this model suggested that when younger individuals had more carryover within one form of affect (e.g., positive to positive affect over time), they exhibited less spill-over (e.g., positive to negative affect over time). Additionally, those with higher trait levels of negative affect experienced more carryover of their negative affect across time. However, for older individuals, those with higher levels of positive affect did not exhibit more carryover of their positive affect. Instead, they exhibited less spill-over from negative affect into positive affect. Additionally, higher mean levels of negative affect were predictive of more carryover of this negative affect for older individuals. These results provide greater nuance, but are largely consistent with results from the fixed effects model, suggesting that, in this study, the dynamics of affect valence did not differ substantially on the group versus individual level (Hamaker et al., 2018). This suggests that the group-level model may be just as informative as individual-level models for studying affect valence over time.

Group (and Subgroup) Iterative Multiple Model Estimation. The above models assume that participants are homogeneous in that they all have the same paths in the model, just with different levels of effect across participants. Recently, methods that do not assume this type of homogeneity have been developed. These methods first were developed for research in neuroimaging but have also been investigated in ecological momentary assessment data and largely rely on a framework called unified structural equation modeling (USEM). USEM combines structural equation modeling (SEM) with VAR to estimate contemporaneous and lagged relationships (Beltz, Beekman, Molenaar, & Buss, 2013; Kim, Zhu, Chang, Bentler, & Ernst, 2007). USEM can be used in both a top-down (i.e., hypothesis-driven) manner that is similar to multilevel methods, or a bottom-up (i.e., data-driven) approach that can nevertheless result in a single multilevel model if that shows the best fit. In either case, different models can be evaluated and compared based on standard fit indices. Notably, USEM has been adapted for a method called Group Iterative Multiple Model Estimation (GIMME; Gates & Molenaar, 2012) and, later, Subgrouping Group Iterative Multiple Model Estimation (S-GIMME; Gates, Lane, Varangis, Giovanello, & Guiskewicz, 2017). GIMME can estimate both group-level relationships and individual-specific relationships and S-GIMME can estimate subgroup-level relationships in addition to the group and individual-specific relationships.

Readers interested in the GIMME and S-GIMME methods are encouraged to review the papers describing the development of these methods (Gates et al., 2017; Gates & Molenaar, 2012). The development of these techniques marks a notable improvement over group-based analyses (e.g., regressions) or multi-level models that can model within-person variance, but not individual-specific relationships. Additionally, GIMME and S-GIMME methods are advantageous in that they can detail how any one individual within the group differs from the overall group. Although GIMME methods are optimal in that they do not require the homogeneity assumption of ergodicity to be met, these methods do assume stationarity. Notably, one method of subgrouping that specifically tests for ergodicity is described by Gonzalez and Ferrer (2014); we have not found another instance of this method being used, but it may also be of interest to readers who are investigating multilevel and GIMME-like methods.

Several studies have utilized the GIMME and S-GIMME methods to analyze group-, subgroup-, and individual-level trends over time. One of the first studies using USEM analyzed gender differences in the levels of positive affect and vigor of activity demonstrated in play behaviors among same-sex groups of young children (Beltz et al., 2013). Results from group-level USEM suggested that for girls (as compared to boys), positive affect from the previous 10-second period predicted positive affect in the current time period (i.e., carryover or a lagged relationship), which the researchers argued was consistent with emotional contagion theories. Additionally, there were no statistically significant differences in the number of contemporaneous and lagged relationships of play behaviors across individuals, again demonstrating that group-level models may reveal similar information to individual-level models, suggesting that positive affect and vigor of activity may operate and relate similarly across younger individuals (Beltz et al., 2013).

Wright and colleagues (2016) used a USEM model to analyze person-specific heterogeneity in daily experiences among individuals with personality disorders. Researchers first used multilevel modeling to determine the presence of a two-factor structure of internalizing and externalizing experiences on the group level, which was further specified by a four-factor model consisting of negative affect, detachment (e.g., social isolation), hostility, and disinhibition (e.g., irresponsible behavior) on the within-person level. Wright and colleagues (2016) then selected four specific individuals and fit the four-factor model for each individual using USEM. Model indices suggested good fit, indicating that this group-level model fit the data from all four exemplar individuals. However, individual-level models suggested that these four individuals displayed different dynamic trajectories of these factors across time. For example, greater negative affect predicted greater detachment for two participants. However, there was a bidirectional relationship between negative affect and detachment for a third participant, and the fourth participant did not demonstrate a relationship between these two factors. This study provides direction for the use of USEM to test specific hypothesis-driven models on the individual level and demonstrates a useful integration of findings from the group and individual levels using appropriate methodology. Moreover, in contrast to the studies reviewed thus far, these results suggest that even though a group-level factor structure may describe each individual's data, the dynamic relationships between these factors differ for each individual.

GIMME methods have also been used to analyze personality traits assessed using daily diary methods. One study assessed daily reports of neurotic personality traits collected from a study by Borkenau and Ostendorf (1998) (discussed earlier) and analyzed using GIMME (Lane & Gates, 2017). Group-level results suggested that irritability predicted vulnerability, which itself predicted emotional stability and feeling more resistant. Researchers included results from one specific individual who displayed these same relationships, in addition to unique idiographic relationships. The fact that the individual displayed some results that were consistent with group trends alongside others that varied from the group may provide suggestions for the clinical utility of such methods. For example, GIMME could be used to compare how this one individual (e.g., a client) compares to other individuals with similar concerns or disorders in a clinic setting, which might be used to support modifications to a treatment regimen for that individual.

Similarly, Beltz and Gates (2017) used GIMME to analyze daily ratings of personality captured using the Neuroticism-Extraversion-Openness Personality Inventory (Costa & McCrae, 1989) and presented both group and individual level findings (Beltz & Gates, 2017). Results from the group-level model suggested that neuroticism negatively predicted agreeableness. Although this relationship was present for all exemplar individuals, the remaining paths in each individual's model varied. For example, one participant's model suggested that extraversion predicted lower neuroticism whereas another participant demonstrated a bidirectional relationship, with both extraversion and neuroticism predicting lower levels of the other construct over time. Another participant did not demonstrate any relationship between these two traits (Beltz & Gates, 2017). This study provides further evidence that although there are some group-level paths in common amongst all participants, the full model for each individual appears idiographic in nature.

Lane and colleagues used S-GIMME to describe results using daily diary data from a subsample of individuals with borderline personality disorder (i.e., the same sample discussed earlier in Wright et al., 2016). Daily responses regarding mood lability, anxiety, depression, anger, impulsivity, emptiness, and urgency were collected and entered into the S-GIMME model (Lane, Gates, Pike, Beltz, & Wright, 2018). Results suggested that mood lability predicted depression over the course of the day and all items exhibited some stability over time (i.e., statistically significant autoregressive relationships). Furthermore, S-GIMME identified three subgroups. The first subgroup was best described by a bidirectional relationship between anxiety and depression at one point in time, as well as associative (i.e., contemporaneous) relationships between anxiety and mood lability, depression and emptiness and anger, anger and urgency, and urgency and impulsivity. The second subgroup was best described by contemporaneous relationships between anxiety and mood lability and impulsivity, mood lability and urgency and anger, and urgency and emptiness. Interestingly, the third subgroup consisted of just one individual (Lane et al., 2018). Empirical results suggest that GIMME methods can be used for ecological momentary assessment data and provide direction for researchers interested in analyzing and comparing how idiographic and group level models differ from each other within the same sample. Results from the multilevel and GIMME studies reviewed here reveal some key differences in findings at the group versus individual level, highlighting the utility of further examination of psychological processes using purely idiographic methods.

Overall, multilevel and group iterative methods allow researchers to parse between and within-person variability and determine whether there is statistically significant intraindividual variability for a parameter within the model. Additionally, because multilevel methods estimate random effects by using group-level data, this reduces the amount of individual-level data needed to run a successful model, which can be helpful when data collection methods are limited. Furthermore, multilevel and group iterative models can be used to investigate group-level differences on individual-level parameters (e.g., gender, age, diagnosis). Likewise, there is preliminary evidence to suggest that multilevel models can even outperform idiographic models under certain conditions (c.f., Liu, 2017). However, the multilevel methods reviewed here are not suited to provide direction on a single individual in isolation and can only estimate effects for individuals based on the assumption that each individual represents a variation from the mean processes of the group. Although GIMME-based models can determine which individuals might need to be modeled separately, they do so based on group analysis as well. As mentioned above, some researchers would argue that such models are not themselves idiographic because they do not model each individual separately. Fortunately, purely idiographic methods are also available. We now turn to a review of these methods.

Fully Idiographic Methods

Idiographic methods have long been used in clinical psychological research. Historical studies using older idiographic methods have typically examined psychotherapy process (see, e.g., Jones, Ghannam, Nigg, & Dyer, 1993; Jones & Nesselroade, 1990; Luborsky, 1953; Luborsky & Mintz, 1972; and Russell, Jones, & Miller, 2007, who provided a review of idiographic methods used to study psychotherapy process). Notably, VAR and other similar time-series methods have been used more recently to study psychotherapy process (e.g., Hoenders, Bos, De Jong, & De Jonge, 2012; Tschacher & Ramseyer, 2009; Tschacher, Zorn, & Ramseyer, 2012). However, due to the systemic nature of changes seen over the course of therapy, time series from individuals currently in therapy do not seem plausible as examples of a stationary process. As a result, we find it implausible that psychotherapy data will meet the assumptions of models that cannot accommodate time-varying components. Thus, for this review, we will examine studies that focused on data that plausibly reflect a stationary or nearly stationary process. This section will provide an overview of the theory behind idiographic methods and will evaluate selected studies that best highlight an idiographic approach, beginning with P-technique.

Raymond Cattell developed P-technique in the 1940's for analyzing correlations among variables across occasions within a single individual (Rovine, Molenaar, & Corneal, 1999). P-technique differs from multilevel methodology in that it provides information about the factor structure of a single individual's responses. In P-technique, the observed time points from a given individual are subjected to exploratory factor analysis (Rovine & Lo, 2012). It is worth emphasizing this point: P-technique is simply an exploratory factor analysis of a single person's data, measured across occasions instead of across people. Notably, P-technique is limited in that it does not explicitly model the dynamic nature of time-series data (Lee & Little, 2012); however, researchers have used both simulation and empirical data to demonstrate that the results obtained using P-technique may not be substantially different than results obtained via techniques that properly account for dynamic relationships (Molenaar & Nesselroade, 2009).

P-technique has been used to evaluate whether the factor structure of personality and affect for specific individuals across time appears to differ from the factor structure determined via differences between individuals in a group (Borkenau et al., 1998; Zevon & Tellegen, 1982). Borkenau and colleagues fit the five-factor model of personality demonstrated in previous group-level analyses to data from specific individuals using P-technique. They demonstrated that this five-factor model fit a majority of individuals' longitudinal data, suggesting that the structure of personality may be similar for most individuals (Borkenau et al., 1998). Similar results were observed for another study comparing the structure of affect. In this study by Zevon and Tellegen (1982), the hypothesized two-factor structure of positive affect and negative affect fit a majority of individual's data when analyzed using P-technique, with only a few exceptions (Zevon & Tellegen, 1982).

Taken together, these studies suggest that the factor structure of certain constructs, such as personality or affect, may not differ substantially across the group versus individual level. However, results from these studies may be limited in that they assessed items at most once a day, which required participants to respond retrospectively over one or potentially more than one day (Borkenau et al., 1998; Zevon & Tellegen, 1982). Additionally, use of a 5-point Likert scale (Zevon & Tellegen, 1982) may have limited the potential for intraindividual variability. Perhaps just as importantly, it is unclear to us whether the factor extraction and rotation methods used were appropriate to the data. These limitations make it difficult to determine whether the similarity in factor structure across group versus individual level is due to these limitations.

More recent work suggests that group and individual-level factor structures may, in fact, differ—at least when the models include additional variables, such as social and behavioral indicators. Wright (2016) aimed to evaluate idiographic patterns of social interactions for individuals with borderline personality disorder. Individuals were instructed to report on affective and behavioral processes after each social interaction for three weeks. Results of P-technique from five individuals suggested that individual structure varied across the participants (Wright, 2016). For example, the participant with the most severe psychopathology had the least defined factor structure (e.g., their model largely consisted of one affect factor). In contrast, the factor structure from the four other participants appeared to also include an interpersonal factor, although content of items for this factor varied across participants. Additionally, models from two participants demonstrated an association between reports of self-harm and affect or interpersonal factors. Through the inclusion of key behavioral indicators (i.e., self-harm), researchers suggested that these idiographic models could provide context for understanding key situations in which participants engage in maladaptive behaviors (Wright, 2016). This information could be used in a clinical setting to help inform functional analysis aimed at reducing and preventing self-injurious or maladaptive behaviors.

These studies demonstrate how researchers can evaluate differences in factor structure on the group versus individual level. However, as previously discussed, P-technique is limited in that it collapses across all time-dependent variables within the time-series and the relationship between two variables at one point in the time series is assumed to be entirely correlational (i.e., not due to effects from the past; Lee & Little, 2012). Therefore, whereas P-technique may be useful for elucidating individual-level factor structure in general, results do not account for how much of the correlation between items might be due to influences between them over time, potentially inflating estimates of correlation (Molenaar, 1985). A separate set of techniques are needed to study intraindividual effects of dynamic relationships over time.

Dynamic idiographic methods assuming stationarity. In this section of this review, we will examine how researchers have used idiographic methods that model dynamic processes but assume stationarity to study longitudinal data. Differences in the methods we discuss in this section largely concern the hypothesized structure of the variables (latent versus observed).[2] Methods using observed variables often utilize VAR, which models lagged and cross-lagged relationships between multiple variables in a given (individual-level) time-series (Brandt & Williams, 2007). A VAR model is constructed via a series of equations in which each variable in the time-series is predicted by a lagged (i.e., previous) version of itself and (typically) all other variables in the time series, and a random error term. This random error term is assumed to be multivariate normal and uncorrelated with other error terms in the model. Although we say that models using *observed* variables often use VAR, it should be noted that all the methods referenced in this review typically use some form of VAR. Time-series methodology is largely similar across latent variable and observed variable (i.e., network) frameworks and the mathematical framework is similar to that of a general autoregressive model. The more important difference between observed and latent variable frameworks is that latent variable models attempt to account for measurement error, whereas observed variable models typically do not (although see Schuurman, 2016; Schuurman, Houtveen, & Hamaker, 2015 for exceptions). Thus, empirical examples of methods that assume latent structure will be evaluated alongside methods that assume an observed or network structure.

[2] Methods using observed variables focus on direct relationships between variables, often reflecting a network framework. The network framework assumes that observed variables (i.e., nodes) direct change across the network (Fried et al., 2016), rather than assuming that the underlying latent variable is responsible for the covariation between the observed variables (Cramer, Waldorp, van der Maas, & Borsboom, 2010). Interested readers are encouraged to read more about the nuances of the network approach, especially similarities and differences as compared to the latent variable approach (c.f., Borsboom & Cramer, 2013; Epskamp, Rhemtulla, & Borsboom, 2016).

One prominent method in this category is dynamic factor analysis (DFA; Molenaar, 1985). DFA was originally developed as an extension of P-technique to properly account for dependency within and across variables in the time series. DFA allows researchers to model the lagged and cross-lagged effects between variables, which prevents the artificial inflation of parameters that occurs when these lagged effects are not modeled (Molenaar, 1985). As such, researchers have often followed P-technique with DFA to examine the factor structure of psychological and psychotherapeutic processes for specific individuals and to model changes in this factor structure over time.

One example of a study in which researchers combined P-technique with DFA examined affect over time in two adolescent stepsons interacting with their stepfathers (Molenaar et al., 1999). Results from the DFA suggested that the two individuals exhibited different factor structures as well as differing relationships between the factors over time. This study emphasized the idiographic nature of emotional reactions to interpersonal interactions, as each stepson demonstrated a unique factor structure, with few shared associations between items and factors. Another study using DFA assessed affective dynamics within a heterosexual married couple each day for a total of six months (Ferrer & Nesselroade, 2003). The wife's level of positive affect on one day predicted level of positive affect the following day, whereas, her husband's level of positive affect on one day predicted level of positive affect two days later. Dynamic cross-lagged relationships revealed that the husband's level of negative affect predicted his wife's level of negative affect and positive affect the following day; however, the wife's affect did not predict her husband's affect over time (Ferrer & Nesselroade, 2003). Both studies provide evidence for the idiographic nature of interpersonal relationships, and this information could be used within the context of treatment planning. For example, idiographic information on emotional reactions within dyadic relationships may help to elucidate underlying patterns of distress (e.g., if one partner's distress reliably predicts another partner's distress at a later time point).

Recently, VAR has also been used in conjunction with P–technique to determine the dynamic factor structure for individuals with generalized anxiety disorder (GAD) (Fisher, 2015; Fisher, Newman, & Molenaar, 2011). Fisher and colleagues (2015) recruited ten participants diagnosed with GAD. These participants completed daily measures of GAD and related cognitive-behavioral factors for approximately two months. Exploratory P-technique was first used to identify the latent factor structure for each individual. Results from P-technique suggested that most participants exhibited three latent factors of symptomatology, although the structure of these factors differed across individuals (Fisher, 2015). Interestingly, results from the P-technique models demonstrated that even though all participants were diagnosed with GAD, only two participants demonstrated a factor that included all diagnostic criteria of GAD. Others demonstrated models that contained the criteria of GAD on separate factors, suggesting that individuals may exhibit different symptom structures compared to the symptom structures outlined in standard diagnostic assessments. These discrepancies may reflect characterological differences between symptomatology characterized in group-level assessments and the unique dynamics of symptomatology for an individual person. However, nearly all models featured a factor that included worry, fatigue, and behavioral avoidance, symptoms consistent with GAD (Fisher, 2015).

Next, factor loadings were analyzed using VAR to assess both the contemporaneous correlations (i.e., at one point in time) and directed relationships across time for each individual. Interestingly, each participant self-reported persistent worry during the initial diagnostic interview; however, results from the time series data exhibited a weak autocorrelation for worry for most participants. This pattern of results may suggest that level of worry one day was not strongly related to the level of worry the following day. Notably, each participant exhibited a different individual-level model. A qualitative examination of the models suggested that that relationships between symptoms varied across individuals (Fisher, 2015). For example, one participant exhibited a model in which worry predicted future procrastination; another participant exhibited a model in which procrastination predicted future worry. Still another participant's model contained only autoregressive relationships and no cross-lagged relationships (Fisher, 2015). This study provides an excellent example of individual differences within a sample recruited based on standard diagnostic criteria and may help to inform future treatment planning. For example, the information that each individual demonstrated different individual-level patterns between their worry and other emotional or behavioral indicators may provide information for tailoring a manualized treatment for GAD.

Fisher and colleagues (2017) conducted a second study and recruited individuals with GAD and MDD who reported on cognitive-affective items four times a day for a month. Researchers analyzed the data using DFA with single indicators (essentially using a VAR model) to estimate lagged effects. Researchers highlighted results from three exemplar participants, each of whom demonstrated a different idiographic model. For example, one participant's level of worry predicted higher levels of concentration and more enthusiasm at the next time point, whereas another participant's level of worry predicted lower feelings of fear at the next time point. The third participant's level of worry predicted lower avoidance of activities at the following time point. Likewise, although two participants exhibited a negative relationship between feeling down and feeling fatigued at the next time point, the third participant's level of negative affect did not predict other variables at the following time point (Fisher, Reeves, Lawyer, Medaglia, & Rubel, 2017). Fisher and colleagues (2017) note that depressed mood and worry were not central or strong predictors of symptomatology across most individuals, which contrasts with their status as hallmark symptoms of MDD and GAD. This study provides additional evidence of idiographic differences in how diagnostic criteria manifests across individuals. Additionally, these results could be used to advise treatment planning and support the use of specific strategies within a manualized protocol for certain individuals.

Wichers and colleagues (2014) used VAR to examine stress-related changes in affective-behavioral ratings over the course of multiple time points within a day in a sample of individuals with residual depressive symptoms (data originally presented in Geschwind, Peeters, Drukker, van Os, & Wichers, 2011). Wichers and colleagues (2014) present both a group-level model and data from two separate individuals. Data from two individuals demonstrated very different models both from each other and from the group. For example, one participant's model suggested that they[3] experienced negative affect in response to social stress. When this individual experienced negative affect, they were also more likely to reach out for social support, a potential sign of effective coping. In contrast, the second participant's model suggested that they experienced decreases in response to social stress. However, positive affect was not predicted by any other variables in the model, suggesting this participant was less resilient to stress (Wichers, 2014).

As discussed previously, the complexity of constructing and interpreting idiographic models reflects one of the main limitations to integrating idiographic methods into clinical settings. However, there have been preliminary strides taken towards automating these methods, which would facilitate integration of these methods into clinical settings. The following two studies utilized an automated web program – autoVAR – designed to analyze ecological

[3]We use "they" because we do not know the self-identified gender of these individuals.

momentary assessment data using VAR approaches (van der Krieke et al., 2015). Researchers demonstrated the use of autoVAR by analyzing time series data from four men who recently suffered from a post-myocardial infarction. The men were asked to rate daily levels of physical activity and depressive symptoms over a three month period (Rosmalen, Wenting, Roest, de Jonge, & Bos, 2012). Results from autoVAR revealed a different model for each participant. For example, for one participant, an increase in the level of physical activity on one day predicted a decrease in depressive symptoms two days later, whereas this relationship was reversed for two other participants (van der Krieke et al., 2015). Thus, if the goal is to decrease depressive symptoms, it is most obvious for the first participant to increase his physical activity. However, for the other two participants, another intervention may be warranted. Additionally, the fourth participant did not exhibit any directed relationships, suggesting that his level of physical activity and depressive symptoms may not be related in a statistically significant way.

In a second study, van der Krieke and colleagues (2017) recruited several hundred participants to complete three daily assessments consisting of affect and behavioral items, along with optional individual items, for approximately one month. Time series data were analyzed using autoVAR and personalized feedback was provided, including descriptive statistics of participation, as well as contemporaneous and directed models of the items. Importantly, participants provided feedback regarding the utility and perceived benefits from the study. Overall, participants responded favorably to the study and did not perceive any change in behavior as a result of the ecological momentary assessment, yet they also perceived limited benefit from completing the assessments (van der Krieke et al., 2017). As this study recruited from the general population, as opposed to a clinical sample, it is possible that perceived benefits of personalized models may be different for those individuals actively seeking therapy. Overall, these two studies provide initial direction to inform how idiographic methods can be integrated into applied and clinical settings.

Time-varying longitudinal idiographic methods. As mentioned above, new methods are being developed for examining and modeling data that violate stationarity. In an empirical study using time varying autoregression (TV-AR), Bringmann and colleagues (2016) tested four different time-varying models in which the intercept parameter, the autoregressive parameter, or both parameters were allowed to change over time. These models were evaluated in two individuals who reported on daily levels of affect (e.g., happiness). The best-fitting model differed across participants. Results suggested that the first participant experienced progressively lower levels of happiness as time went on. In contrast, results suggested that the second participant experienced a change in levels of happiness and that this change was non-linear in nature (Bringmann et al., 2016). Bringmann and colleagues (2016) explain that these changes would not have been detected using more traditional time-series methods and highlight the sensitivity of the TV-AR method to modeling nonlinear changes in time. However, TV-AR is limited in that it can only model a single variable over time. A second technique, time-varying vector autoregression (TV-VAR), is a more flexible method for studying a time-varying multivariate time series (Bringmann, Ferrer, Hamaker, Borsboom, & Tuerlinckx, 2018; Haslbeck, Bringmann, & Waldorp, 2017). However, time-varying methods often require a large number of observations (based on experience and discussion with researchers, our best guess is that over 100 time points may often be needed; L.F. Bringmann, personal communication, July 6, 2018).

Bringmann and colleagues (2018) present results from a TV-VAR, which was used to model changes in the daily positive affect and negative affect of a heterosexual couple. Time-varying effects demonstrated that in the beginning of the study there was considerable carryover between the male partner's positive affect and his level of positive affect the day before. However, as the study continued, his positive affect was better predicted by spill-over from his female partner's level of positive affect the previous day, such that when she was experiencing low positive affect on one day, he would experience higher levels of positive affect the following day (Bringmann et al., 2018). These changes in affective dynamics could not have been captured using standard VAR models, as VAR would have produced irrelevant estimates, underscoring the limitation of modeling only simple linear relationships in constructs over time.

Additionally, Hamaker and colleagues (2016) collected data on daily affect from three patients with bipolar disorder and eleven individuals without the disorder. Researchers used a data-driven approach to fit five different time-varying models to each individual's data and used fit indices to compare model fit within the nested models. Overall, they demonstrated that the best-fitting model varied across individuals. For example, results from a regime-switching model suggested that the switch between affective states was linked to large changes in positive affect for individuals with bipolar disorder; whereas, for control participants, the switch between affective states was associated with changes in negative affect. Results from the vector autoregressive integrated moving average model suggested patients with bipolar disorder who experienced large changes in affect were slower to return to their affect baseline as compared to the individuals without the disorder. This study represents a data-driven attempt to use time-varying methods to capture variability across individuals and may help illustrate idiographic assessment of bipolar psychopathology. Furthermore, these results suggest that there may be notable differences across individuals, as evidenced by differences in model fit amongst the models tested (Hamaker, Grasman, & Kamphuis, 2016).

Integration into Clinical Settings: Strengths and Limitations of the Idiographic Approach

As previously discussed, idiographic methods show great promise for integration into clinical settings and, indeed, some of the studies here have already been conducted with the intention of using results for clinical purposes. However, before these methods can routinely complement clinical work, there are limitations and potential barriers that must be resolved. One of the primary limitations of idiographic methods is that time-series analyses requires collection of numerous data points to construct a model. Another limitation is that the model can only be as accurate as the variables included in the model. Thus, the therapist will need to use clinical judgment to determine which variables would be most useful to include and may need to rely on patient insight to identify which symptoms or constructs are most central to distress. Clinician-scientists will need to strike a balance between assessing in accordance with the theoretical frequency of change and the practical limitations of collecting time-series data. Although smartphone apps are being developed for personalized assessment, effective implementation necessitates an effort to determine which items and what time frame should be assessed. Finally, if therapy is successful, symptom processes will systematically change over the course of therapy, potentially violating stationarity. These concerns and limitations will need to be resolved before idiographic models can readily be implemented in clinical settings.

Importantly, much of the research discussed here provides primarily theoretical discussion of integrating idiographic methods into treatment. With the exception of the autoVAR studies discussed earlier and the numerous case studies using idiographic methods (cf. Russell et al., 2007), the updated idiographic methods discussed here have not been systematically implemented for use in clinical settings. Additionally, we do not know of any published empirical studies that have evaluated the efficacy and feasibility of these methods in clinical practice, although there are signs this is changing. Multiple groups (including our own) are currently investigating how these methods can be integrated into clinical settings and evaluating the feasibility and accessibility of these methods to clinicians. We find it plausible that such methods will be useful and are hopeful that idiographic methods may be able to supplement empirically supported treatment by adding an individual-level and data-driven approach, potentially resolving errors in clinical judgment and treatment planning as a result of low insight or clinician biases. Thus, idiographic research has the potential to transform psychopathology and psychotherapy research much in the same way that precision medicine has reshaped the field of medical oncology (Collins & Varmus, 2015).

Most importantly, individual-level designs represent an answer to the call for increased idiographic focus that has continued for decades (Barlow & Nock, 2009). In a field that was initially commissioned to identify the particularities of human nature (Lamiell, 1998), the individual-level designs reviewed here represent a data-driven way forward in studying the individual. Indeed, these designs have already been used for decades to study psychological processes, suggesting that clinicians and clinical scientists alike are open to integrating these methods into clinical practice. With the advent of ecological momentary assessment smart-phone technology, open-access software for analyzing time-series data, and more advanced statistical methods, a true integration of individual-level designs into clinical practice may now be achievable, with the potential for improvement of existing psychological models and psychological care.

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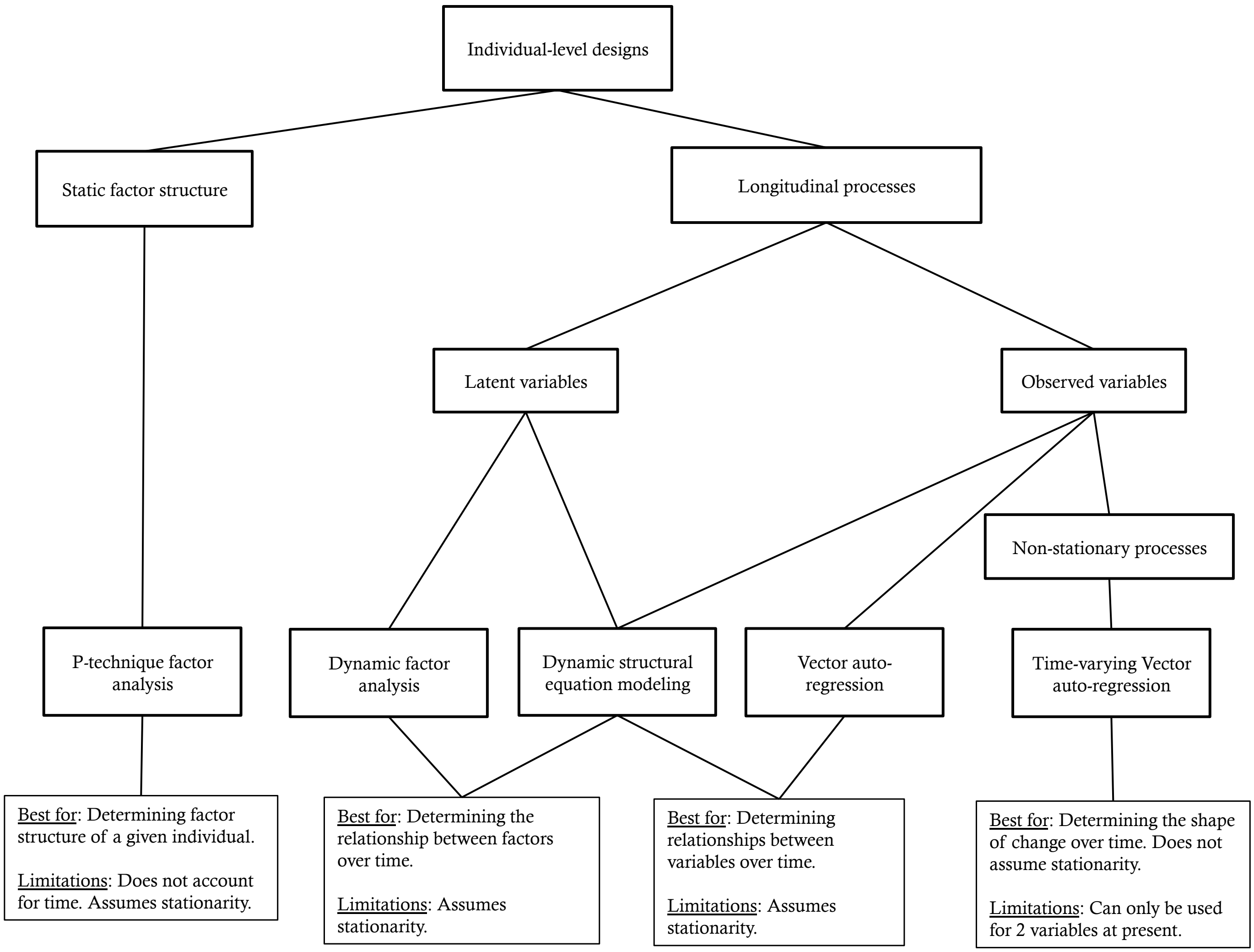

Figure 1. Diagram describing different types of idiographic analyses. Note that methods, including P-technique factor analysis, dynamic factor anlaysis, dynamic structural equation modeling, and vector auto-regression have been used most frequently in the idiographic literature. However, time-varying vector autogression shows considerable promise due to the ability to handle nonstationarity.

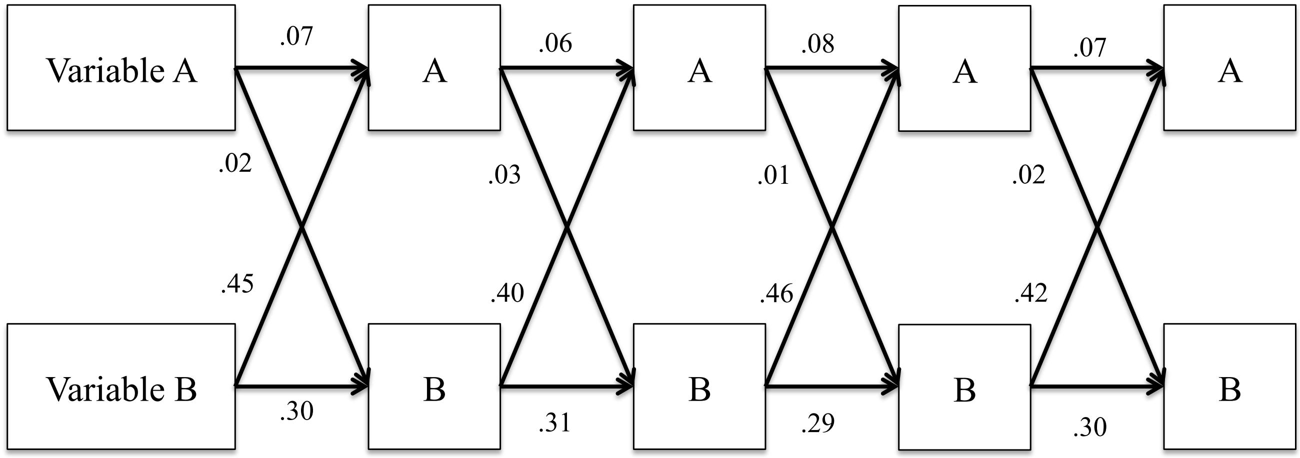

Figure 2. Visualization of Granger causality.

Note. This time-series depicts the lagged and cross-lagged relationships between variables A and B at a series of time points. This presence of a cross-lagged relationship between Variable B and A even after accounting for the lagged relationship of Variable A suggests that the relationship between Variable B and Variable A exhibits Granger causality. Note that the modeled process is only approximately stationary, in that, for example, the relationship of Variable A with itself is not precisely the same at each time point. Although it is possible to allow this variation in group-based models, if these variables were being examined in an individual over time, stationarity would be both assumed and enforced unless a time-varying method was specifically examined.