Dynamic Network Analysis

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Abstract

Psychological dynamics are central to psychological theories. However, the methods for capturing psychological dynamics have lagged far behind the theories, leaving researchers to rely on non-dynamic methods for theory testing and building. Such a mismatch between theories and methods creates a gap that can threaten the psychological process. From the perspective of a long-time theory-method gap in personality psychology, this chapter illustrates how dynamic methods can help to close the theory-method gap. We review four statistical methods for estimating dynamic networks from time series of data of active and passing sensing: association networks, graphical vector autoregressive models, unified structural equational models, and dynamic exploratory graph analysis. Using a focal participant, we demonstrate shared and unique features of each of these methods, make recommendations for when to each of these models, and highlight a number of core challenges these and other dynamic methods will have to tackle moving forward.

Dynamic Systems Analysis

Since the rise of empirical psychology in the 19th century, psychologists have attempted to specify theories of psychological processes and phenomena, including consciousness (Wundt, 1911), attitudes (G. W. Allport, 1954), personality (e.g., G. W. Allport, 1960; Baumert et al., 2017; Beck & Jackson, 2020a, 2020b), work performance (Campbell & Wiernik, 2015; Dalal et al., 2014), intergroup processes (F. H. Allport, 1920), and more. A common feature of these theories is that they specify how one or more psychological processes and/or phenomena unfold over short and long time spans. In other words, psychological theories are dynamic. For example, theories of personality suggest that personality should drive the types of situations individuals select into (e.g., Emmons & Diener, 1986), that individuals should modify the situations they encounter (e.g., Funder & Colvin, 1991), and that situations should impact both personality as a stable entity (e.g., Wrzus et al., 2016) as well as its expression (e.g., Sherman et al., 2015). Moreover, these theories also suggest that how individuals navigate these patterns between personality and situations reflects personality itself (e.g., Mischel & Shoda, 1995). Despite this, personality is typically studied by looking how broad, aggregated, and often decontextualized personality traits (1) predict the life events people experience (e.g., Beck & Jackson, 2021), (2) change over time (e.g., Graham et al., 2020), and (3) are predicted by events or experiences individuals have (e.g., Bleidorn, 2012; Bleidorn et al., 2013). Thus, the dynamic nature of the theory is not reflected in either the measurement or modeling of personality specifically and psychology more broadly, which has led to a widening gap between theories of psychology and the methods applied to test them. But such gaps between theory and method in psychology can have great consequences for theory building and testing.

In this chapter, we will address the theory-method gap in psychology from the perspective of the study of personality. We will summarize broad classes of dynamic psychological theories in personality, how challenges to collecting dynamic data have widened the theory-method gap, how active and passive mobile sensing data have the opportunity to close this gap, and how dynamic networks can aid analyzing and interpreting such data in alignment with dynamic psychological theories. We specifically highlight four network models: graphical vector autoregressive models (graphical VAR), unified structural equation models (uSEM), and dynamic exploratory graph analysis (dynEGA), and how dynamic theory can guide associated analytical decisions. Finally, we will close by connecting these back to psychology more broadly.

Personality Dynamics

Allport and the Rise of Personality Theory

The role of dynamics in the study of personality goes back to its earliest days of personality psychology, Gordon Allport, one of the “Fathers” of personality as an empirical discipline (e.g., G. W. Allport, 1937), wrote about personality as a dynamic phenomenon. As he defined it, personality was “the dynamic organization within the individual of those psychophysical systems that determine his unique adjustments to his environment” (Allport, 1937, p. 48). Each piece of this definition deserves consideration and underscores dynamic elements of personality theory. First, the definition explicitly uses the word dynamic, implying that personality is not simply a static factor over time. Second, personality is an organization, or structure, albeit a dynamic one. Third, personality exists within the individual, or is idiographic or person-specific. Fourth, what makes up the structure of personality is (psychophysical) systems, meaning that the structure (or the organization of features that are relevant) within an individual may dynamically shift over time and across situations. Finally, personality is explicitly about unique adjustments to the environment, which are likely to be unique to them. In other words, transactions with the environment are also best considered idiographically.

Despite this dynamic core of one of the earliest theories of personality by a founder of the field who remains heavily cited to this day, the personality literature over the past century largely concerns studies of population-level (i.e. variable centered, nomothetic approaches) personality traits and their relationship to outcomes (e.g., Beck & Jackson, 2021), how they change (e.g., Graham et al., 2020), and what they are associated with more broadly. This is a strong contrast to the person-level (i.e. person centered, idiographic approach) that Allport advocated for in his definition of personality. Some have labeled this contrast the two sciences of personality – one whose goal was to describe how people differed from one another on shared attributes (a nomothetic approach) and another whose goal was to describe and explain individuals holistically (an idiographic approach), with a focus on why people behaved similarly or differently across time and contexts (see Beck & Jackson, 2021b; Winter & Barenbaum, 1999).

To Allport (1937; 1968), what these nomothetic approaches captured were not the dynamic structures alluded to in his definition. Instead, these “common” traits capture measurable aspects of psychological experience and behavior that are often experienced or exhibited by many people similarly. In other words, common traits reflected similar idiographic traits (and variability in those traits) across people, but, as they reflect idiographic traits, such common traits have no true (i.e. causal) reality of their own. Instead, Allport (1960) saw personality as an open system made up of a number of other psychophysical systems. Indeed, he laid out theoretical evidence of ways in which personality theory and research adhered with main criterion of open systems: (1) input and output of both energy and matter; (2) homeostasis (i.e.

equilibria) are both achieved and maintained even across great disruption; (3) there is an increase in order of the system over time; (4) and there are transactional relationships with the environment (Allport, 1960). He also argued that nomothetic conceptualizations of personality were a closed system that were a consequence of the open system nature of idiographic personality.

Cattell and the Data Box

Despite his theoretical contributions to personality, Allport did much less to test those theoretical propositions. For example, how we could measure and model personality idiographically and link that with nomothetic personality traits was largely not addressed. Instead, work by Raymond Cattell largely structured work toward measuring and modeling personality at different levels of aggregation. In introducing the *data box*, Cattell (1946) argued that persons could be conceptualized into 3-dimensions that indexed people (P_1 to P_N), variables (X_1 to X_p), and occasions or time (T_1 to T_t). Different ways of "slicing" or aggregating across dimensions of the data box reflected the wide array of questions psychologists could ask and answer. For example, typical nomothetic questions focus on the person (P) and variable (X) dimensions and aggregate across the occasion (T) dimension, thereby addressing the question of the structure of individual differences within a population of people, which he termed *R-technique* (See Figure 1).

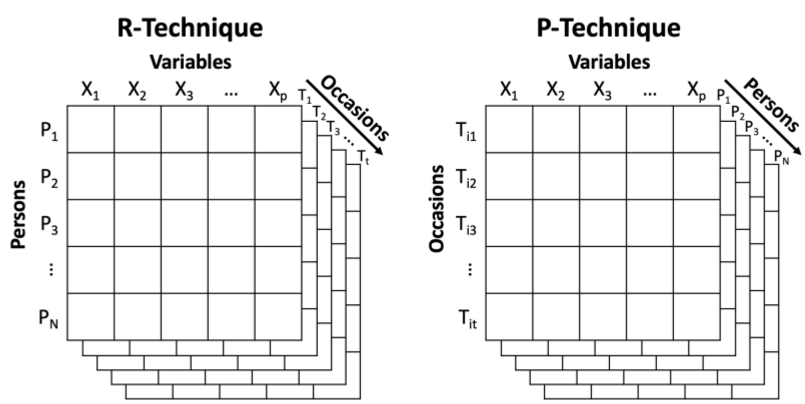

Figure 1. Two ways to “slice” the Cattell’s (Cattell, 1946b) data box to produce R-technique (nomothetic) and P-technique (idiographic) factor analytic structures. In R-technique, one collapses across or slices across the occasions dimension (T) to get the common structure of variables across people, perhaps solely applicable to a particular time or population. In P-technique, one slices across individuals to find the unique structure of variables within a particular person across time.

Cattell’s work on the data box and factor analytic approaches moved both the science of between person differences and the study of idiographic personality dynamics forward. Indeed, he formalized methods for estimating idiographic personality structure by slicing the data box into variable (X) and occasion (T) dimensions and fixing the person dimension, (See Figure 1). This slicing of the data box he termed *P-technique*, in which factor analytic models were applied to X x T matrices for individual people (Cattell, 1943). However, the goal of *P-technique* was to reduce the data to smaller clusters that could be subsumed under a single label rather than to understand the dynamic complexities of how the underlying indicators unfolded within and across people. Such methods would emerge later and will be the focus of later sections.

Challenges in Dynamic Data Collection

One major factor in the theory-method gap in the study of personality has been that the available means for and methods of collecting dynamic data have been quite limited. Empirically understanding how personality unfolds over time often requires time series data, and most statistical techniques require rather large sets of data in order to be able to capture and uncover dynamic features well. But the rise of smartphones has created new opportunities for psychological researchers to collect dynamic data in everyday life. First, the Experience Sampling Method (ESM; Csikszentmihalyi & Larson, 1987), which we will refer to as “active sensor data” because it requires participants to actively provide responses, allowed researchers to collect repeated samples of sets of variables from an individual multiple times within or across days or weeks. Second, smartphones are also constantly collecting so-called “passive sensor data," including audio data (from microphones), accelerometer data, location data, and social media posts, among others. Finally, smartphones and computers can be linked to other passive sensor devices, like physiological monitors of heart rate, blood pressure, skin conductance, sleep quality, movement, and more.

Together, these new sources of data provide a unique opportunity to capture times series data that can be used to better understand personality – and other psychological, social, and biological phenomena – more dynamically. The collection of such data open up new opportunities for assessing all the dimensions of Cattell's data box by making it easier to collect multiple observations (T) from different individuals (P) across sets of variables (X). In other words, researchers could tackle large dimension Person (P) x Observation (T) questions, fixing the Variable (X), among others.

Recent Work on Within-Person Personality Processes

Although Allport and Cattell, among others, advocated for the consideration of dynamic and dispositional approaches to understanding personality, the latter half of the 20th century saw personality largely diverge on two tracks – one interested in how personality unfolds over time and another examining personality as broad, aggregated traits. Fueled by the rise of the experience sampling method in particular, an emphasis on within-person variability began to work its way back into personality near the turn of the century. In the 1970s and 1980s, both Zuckerman (1979) and Buss & Craik (1980) had contended that personality traits were aggregates of personality states. At the turn of the 21st century, (Fleeson, 2001) updated this proposition and demonstrated its empirical validity using ESM data. This and later empirical work later became the basis of Whole Trait Theory (Conner et al., 2009; Fleeson, 2004; Fleeson & Jayawickreme, 2015). Means, standard deviations, and other density distribution parameters of personality states captured the descriptive properties of personality, while leaving the explanatory properties of personality largely open.

In addition, increased computing power made regression-based techniques for dealing with dynamic, time series data in which participants have multiple observations more available. Statistically, such data are considered nested, with observations nested within person. Nested data violate assumptions of independence of errors in basic linear regression and require specialized methods, like multi-level modeling (MLM). Unlike basic regression, MLM allows one to estimate different error terms for observations and units / groups (i.e. persons), thus, explicitly modeling within-person variability (Snijders & Bosker, 2011) [note to editor: add references Dynamic SEM chapter in editing phase]. Moreover, it allows researchers to condition such variability on broader, person-level phenomena and as well as momentary factors. As such, some have argued that MLM is “idiothetic” and helps to bridge the gap between nomothetic assessments of personality that focus on between-person differences and idiographic assessments of personality that focus on within-person variability (e.g. Conner et al., 2009).

Personality: Descriptive, Predictive, and Explanatory

Despite its promise, MLM is a statistical model; that is, a tool to test theories, not create them. Stated simply, a statistical method alone cannot dissolve idiographic-nomothetic tensions (see Fried, 2020) without having a clear and precise link with theories of personality. Many personality theorists have clearly argued that personality states vary over time and should be connected to personality traits (e.g., Baumert et al., 2017; Fleeson, 2001; Fleeson & Jayawickreme, 2015), but the links these theories offer for why states are linked to traits do not align with the theories. Indeed, the data generating process, such as the open system Allport (1960) argued for, of the unfolding of complex psychological phenomena are unlikely to be captured with MLM. Several researchers have laid out evidence suggesting that using between-person models, like factor analysis and MLM, to investigate "within-person processes," which are often thought be the data generating entities, is often misleading and does not allow for strong (causal) conclusions (Borsboom et al., 2003; Fisher et al., 2018; Molenaar, 2004). Such an observation should not be taken lightly, as it suggests that inferences based on between-person models may be misleading at best and wholly incorrect at worst, which could lead to a new kind of credibility crisis in psychology (Moeller, 2021).

Dynamic Methods for Mobile Sensing

In the first sections, we argued that psychology is facing a gap between theory and methods. Then, we briefly introduced challenges to collecting data for answering dynamic questions as well as a small subset of methods often applied to dynamic data. Using personality as an example, we detailed work on the dynamic nature of personality theories as well as how factor analysis and latent traits are not good candidate data generating (i.e. explanatory) models for personality, as well as most psychological constructs. In this section, we next detail a different class of methods that rely on dynamic systems theories and network analysis that show promise for closing the theory-method gap when integrated with mobile sensing data. Before beginning, we want to note that although the methods detailed below draw upon machine learning methods in some cases, we will be focusing on time series and dynamic systems model approaches, leaving the detailing of machine learning methods to other chapters in this volume [note to editor: add references to other volumes in production] and elsewhere (e.g., Renner et al., 2020).

First, network approaches provide a framework for thinking about psychological measurement that extends across levels of multiple dimensions of the Cattell's data box. Based in dynamic systems theory, a network approach asserts that latent traits are emergent properties of interactions among a set of indicators, rather than simply as how levels of a variable tend to discriminate among individuals (e.g., Cramer et al., 2012). In other words, such models assume that indicators, not latent traits, are causal, and that the processes through which latent traits emerge as measurable phenomena emerge from reliable patterning among indicators that have diverse causal underpinnings.

Network approaches have seen an explosion (e.g., Robinaugh et al., 2020), with some touting the great advantages these models offer (Beck & Jackson, 2021d; Borsboom & Cramer, 2013; Cramer et al., 2012), and others some of the downfalls (e.g., Forbes et al., 2019, 2021; although see Jones et al., 2021 for a rejoinder), particularly in cross-sectional research that does not utilize time series designs. Such cross-sectional work can, in some cases, merely reify methods and findings of existing structural theory-method gaps in the guise of using models used in the study of dynamics. Networks highlight and summarize relationships among indicators, visually and quantitatively representing relationships between indicators that reveal both direct (i.e. relationships between two indicators) and indirect (i.e. relationships between two indicators separated by one or more intermediate indicators) relationships between them. However, only a few studies have used network approaches to examine personality (e.g., Beck & Jackson, 2020a, 2021d; Christensen et al., 2019; Costantini et al., 2019; Wright et al., 2019). Despite the promise of these studies, the dearth of research on this topic makes it unclear to what extent networks approaches apply to time series of passive and active mobile sensing data.

Importantly, a network approach is not a single model; there are a growing number of instantiations and parameterizations of network-based models, four of which we will focus on in the present paper: correlations, graphical vector autoregressive models (graphical VAR), unified structural equation models (uSEM), and dynamic exploratory graph analysis (dynEGA). Rather, network approaches, much like other structural methods like factor analysis, are a set of statistical tools that can be applied to the pairwise relationships among a number of indicators, typically structured as matrices. And the models that underlie them are those that result in such matrix-structured estimates. Broadly, the rows and columns indicate the nodes (or variables) under investigation while the cells of the matrices represent the edges (or relationships) among the nodes. Below, we will demonstrate each of these four methods using an example participant from Beck and Jackson (2020a). In that paper, Beck and Jackson (2020a) demonstrated each of these methods but dynEGA. The present paper additionally extends this to dynEGA and includes a more detailed comparison of each. The data come from a longitudinal experience sampling study of personality that collected nine indicators of four of the Big Five (Extraversion [2], Agreeableness [2], Conscientiousness [2], and Neuroticism [3]) four times per day (approximately four hours apart) for two weeks. This resulted in a multivariate time series for each participant with p = 9 indicators and t = ~56 time points. Although this example uses active sensor data, passive sensor data can also be readily incorporated into each of these models.

Concerns and Considerations in Node Selection

Before considering each of the methods, we first want to highlight that a critical part of matching theory and methods is also the design and measures of a study. Indeed, theory-method gaps can also arise when the indicators or variables used are not in alignment with theoretical propositions. Thus, perhaps the most important question when considering whether to represent and understand data or models from a network perspective, concerns the definitions of the nodes and edges (Beck & Jackson, 2021d; Piccirillo et al., 2019) – that is, what are the indicators (nodes) and the relationships among them (edges)? For example, should the lowest-level measurement unit be raw mobile sensing data, or should the data be composited into higher-order constructs (e.g., to reduce multicollinearity a priori)? Just as important as the definition of the nodes is the definition of the edges, which can represent adjacency (or co-occurrences), correlations, partial correlations, frequencies, individual differences, and more (see Beck & Jackson, 2021c; Wood et al., 2017). Moreover, the edges can represent different time scales. Contemporaneous (also known as lag 0; *while* relationships) relationships estimate probabilistic within-person same time point relationships – that is, the tendency for two manifestations of personality to occur at the same time (i.e. co-occur) – and can be thought of as “while” relationships. Lagged and cross-lagged relationships (also known as lag 1 or simply “lagged”; *if…then* contingent relationships), in contrast, estimate probabilistic within-person, cross-time point and cross-indicator (or cross-lagged) relationships – that is, the tendency for two manifestations of personality to follow the other across measurement occasions – and can be thought of as *if…then* relationships, partialling out associations with other features (e.g. Wright & Mischel, 1987). Below, we will integrate these within the discussion of each method, beginning with introducing basics of networks in the association networks before linking these to personality theory.

Association Networks

The simplest time series procedure for constructing a “dynamic” network is zero-order correlations among the variables (X) dimension across the time (T) dimension for each person individually (see Figure 2a). Called “association networks,” these are the correlation matrices that *P-technique* factor analysis (or any other form of factor analysis or principle components analysis) attempts to reduce. Figure 2 shows a visual representation of the steps from raw data to representing person-specific correlations as a network.

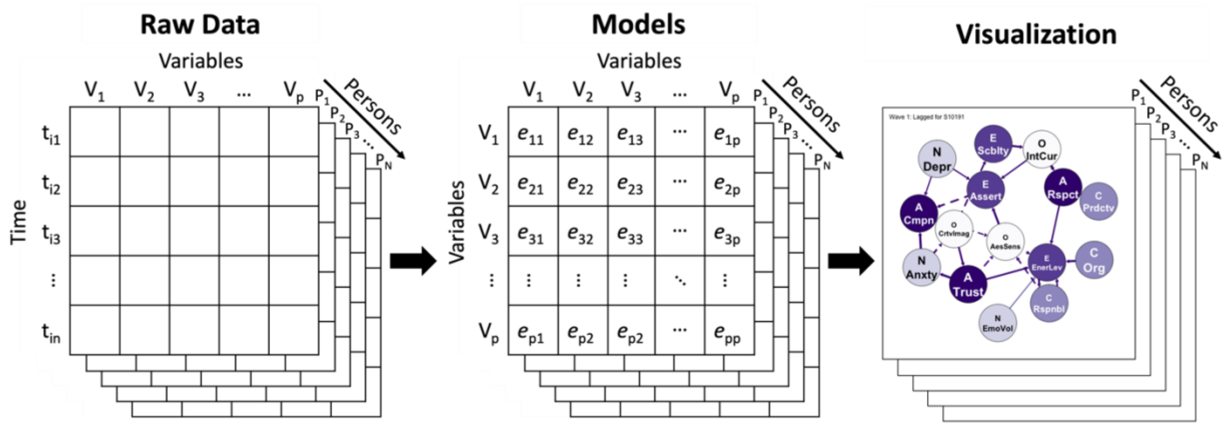

Figure 2. A simplified analytic procedure for using network tools on idiographic time series data from raw data (left) to modeling relationships among variables (V_1 to V_p) and formatting them as a matrix (middle) to visually displaying them as a network.

These association networks traditionally focus on concurrent associations among psychological, behavioral, or other states, which results in a symmetric matrix. But the data can also be lagged in order to look at bidirectional associations among the indicators (i.e. a non-symmetric matrix). Relative to zero-order association networks, cross-lagged networks have some advantages. They are more dynamic by considering how levels of states are associated across time, rather than at the same time. Because most psychological theories concern the changes in states, cross-lagged models come closer to aligning with theories.

Moreover, they offer a method for testing complex sets of relationships that are a hallmark of many key models of personality (G. W. Allport, 1937; Cervone, 2005; Mischel & Shoda, 1995), thus providing initial inroads for closing the theory-method gap in personality. Such relationships are complex not only in that they can include a large number of predictors but also in what those predictors are. For example, within such a framework, one can include different forms of active and passive sensor data, such as ESM, location data, heart rate, and more.

How do such models help close the theory-method gap? To illustrate, we will consider a dynamic theory of personality and how these methods can be applied. Conditional frameworks of personality (J. C. Wright & Mischel, 1987) propose that personality can be conceived of as *if…then* relationships between behaviors and contexts. *If… then's* are also reflective of an open systems perspective (i.e. external influences impact the system but it retains its coherence; G. W. Allport, 1960). When conceptualizing cross-lagged VAR models in these frameworks, we see how these models, coupled with sensor data, close the theory-method gap. Lagged relationships can capture *if…then* contingent relationships, while contemporaneous associations capture *while* relationships. In other words, cross-lagged VAR models allow personality researchers to test for conditional associations that characterize the study of how personality unfolds in the context of individuals' daily lives.

For example, the first row of Figure 3 shows and the contemporaneous and lagged association network of one participant. Because association networks allow all pathways to estimated (i.e. there is no feature selection procedure), all edges are plotted. To help ease understanding of the visualization, stronger associations have darker and thicker lines, positive associations have solid lines, and negative associations have dashed lines. There is, for example, a dark, thick, and dashed edge between two indicators of Conscientiousness, reliable and lazy, which indicates that *while* this participant felt they were not reliable, they also felt lazy and vice versa. The dark, thick, and solid edge between reliable (Conscientiousness) and outgoing (Extraversion), in contrast, indicates that *while* this participant felt outgoing (E), they also felt reliable (C) and vice versa. Of all the nodes, the reliable (C) node has the darkest, thickest edges between it and other nodes, which indicates that many of this participant's other experiences tended to covary with how reliable they felt.

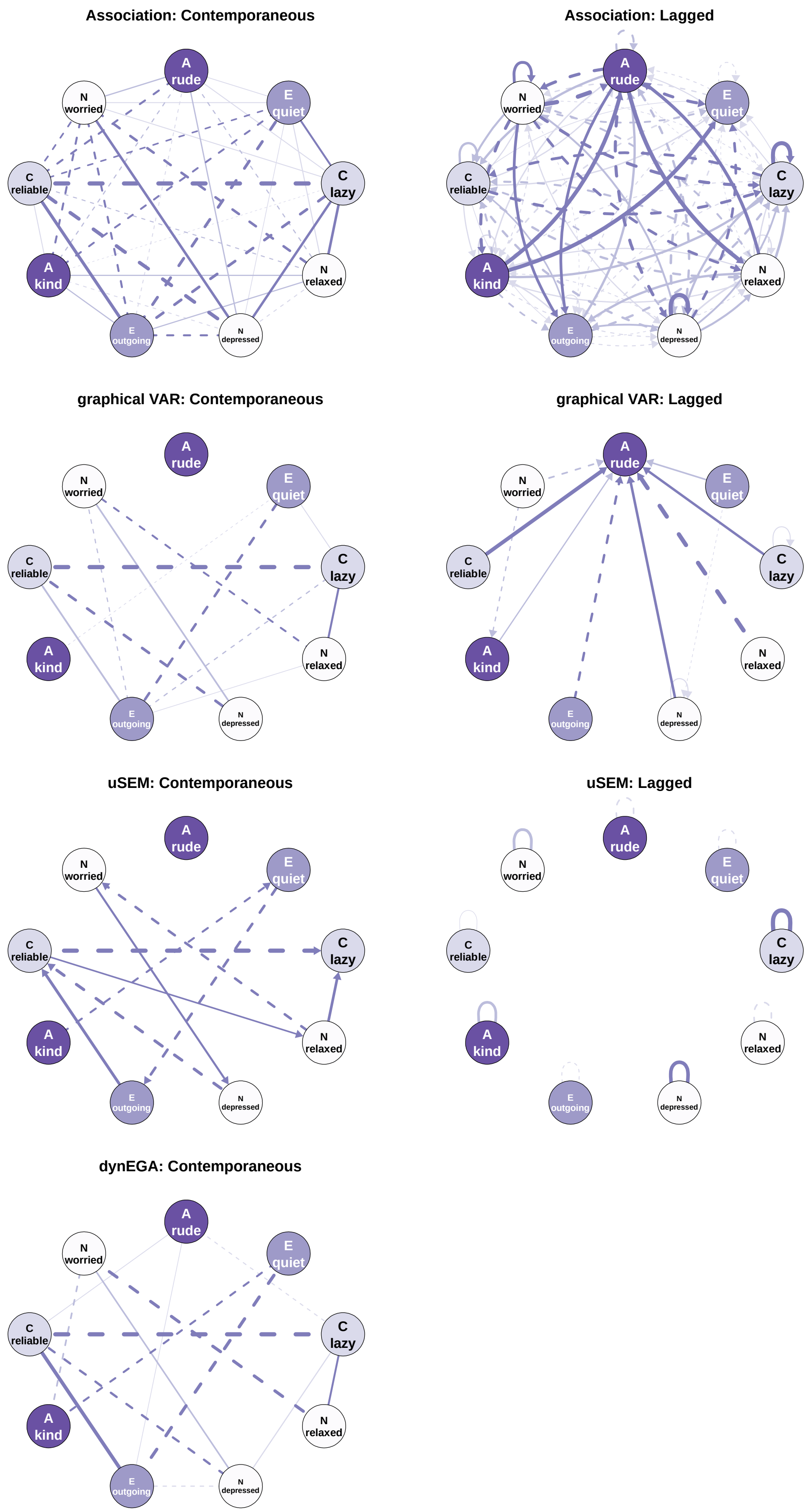
Association: Contemporaneous
Association: Lagged
graphical VAR: Contemporaneous
graphical VAR: Lagged
uSEM: Contemporaneous
uSEM: Lagged
dynEGA: Contemporaneous
A rude
N worried
E quiet
C reliable
C lazy
A kind
N relaxed
E outgoing
N depressed

Figure 3. Sample network visualizations of four different network models: association networks (top row), graphical vector autoregressive (graphical VAR) models (second row), unified Structural Equation Models (uSEM; third row), and dynamic exploratory graph analysis (dynEGA) using generalized linear local approximation of derivatives (GLLA; bottom row). For each, the right column indicates contemporaneous (lag 0, *while*) relationships among indicators, while the left column indicates lagged (lag 1, *if…then*) relationships among indicators.

In the lagged networks, there are also arrows on the edges, indicating the temporal direction of the effect. As can be seen in the figure, the worried (Neuroticism) node has dark, thick dashed lines from it to lazy (Conscientiousness), rude (Agreeableness), relaxed (N), and kind (A). In other words, *if…* someone was worried (N) at present, *then* they would be likely to be less lazy (C), rude (A), relaxed (N), and kind (A) at the next time point. Other nodes, like outgoing (E) have think pale extending from it, suggesting that it does not strongly predict experiences at the next time point. It also suggests that there were a number of strong reciprocal effects, including the strong positive one between rude (A) and relaxed (N), suggest that *if…* this participant was more relaxed (N) now, *then* they were rude (A) later and vice versa. Finally, there were a number of self-feedback-loops, which are often thought of as inertia in the emotion literature. When positive, like the one for lazy (C), this indicates that laziness was a self-perpetuating cycle (Ong & Ram, 2017). *If…* they acted lazy, *then* this participant was likely to continue to do so. Negative feedback loops, like the small one for quiet (E) are thought to represent negative reinforcement cycles (Hamaker et al., 2016). In this case, it could indicate that being quiet had negative consequences such that the participant was likely to change their behavior.

Association networks, which are based on zero-order correlations, have some disadvantages, particularly when there is overlapping variance among the indicators. Thus, some have argued for the importance of examining the unique relationships among the indicators using partial correlations or regression (e.g., Epskamp & Fried, 2018). In such cases, the possibility of over-controlling or overfitting the model increases (assuming the number of observations remains constant). Recently, there have been a number of proposed models for examining such complex models without overfitting, which we will detail now: graphical VAR, uSEM, and dynEGA.

Graphical Vector Autoregressive Models

New techniques for the basic lagged, or vector autoregressive (VAR) model (e.g., Bringmann et al., 2016; Epskamp et al., 2018; Gates & Molenaar, 2012; Wild et al., 2010), have been proposed and implemented (in a limited manner) to account for dynamic relationships among predictors. Typically, these use some method for pruning model pathways to prevent or reduce the effects of multicollinearity (e.g., graphical LASSO; Friedman et al., 2008). These methods produce partial correlations or multiple regression coefficients, which capture the unique relationships among diverse phenomena that may influence manifestations of psychological phenomena.

Graphical VAR uses a two-stage procedure to estimate two networks: a within-time, contemporaneous network (i.e. a symmetrical matrix) and an across-time, cross-lagged network (i.e. a non-symmetrical matrix; Epskamp et al., 2018; Wild et al., 2010). The lagged and contemporaneous networks are estimated sequentially, such that lagged networks are estimated by regressing each indicator on all other indicators (including the focal indicator itself) at the previous time point and contemporaneous networks are estimated using the concentration matrix (i.e. the inverse) of the residual covariance matrix of the lagged networks to detrend participants responses (e.g. Flury & Levri, 1999).

To prevent overfitting, these models are regularized using a variant of the *least absolute shrinkage and selection operator* (LASSO; Tibshirani, 1996), graphical LASSO (glasso;

Friedman et al., 2008). Essentially, regularization uses a constraint to prevent overfitting. Edges that fall below the constraint are set to 0, which effectively reduces the dimensionality of the network by eliminating the estimation of these pathways. glasso includes a tuning parameter that can be set to control the sparsity of the network (the dimensions that are set to 0). The best fitting network is found by testing a range of penalty parameters (lambda) for both the contemporaneous and lagged networks and using an information criterion to compare the models at different values of the tuning parameter. Different values of the hyperparameter gamma can be chosen to optimize prediction accuracy to minimize an information criterion, such as the Bayesian information criterion (BIC) or the extended BIC (eBIC; Chen & Chen, 2008). Notably, when the hyperparameter gamma is set to 0, the information criterion is simply BIC.

Graphical VAR produces two sets of p x p matrices of partial correlations, symmetric partial contemporaneous correlations (PCC) and asymmetric partial directed correlations (PDC), which are derived from the regression coefficients. First, the PDC's are calculated by rescaling the regression coefficients using the residual variances on the diagonal of the residual covariance matrix. Next, the PCC's are estimated by taking the inverse of the residual covariance matrix (see Wild et al., 2010).

The resulting networks from the graphical VAR procedure can be understood similarly to the association networks presented in the previous section. However, there are three key differences. First, rather than zero-order correlations, these networks represent the partial correlations between each of the indicators after partialling out overlapping with variance with all other indicators. Second, because graphical VAR uses regularization to constrain the edges, not all edges are present. Third, the contemporaneous network is based on the residuals of the lagged network. As a result, the contemporaneous network in Figure 3 can be interpreted as *while* relationships. For example, *while* this participant felt lazy, they tended to not feel lazy or depressed. However, how reliable they felt had no association to how worried they felt, but *while* they felt worried, they felt more depressed and less outgoing.

The lagged network suggests a different, more interpretable pattern than the association network. As is clear in Figure 3, almost all of the edges point toward the rude (A) node. In other words, *if…* this participant felt quiet (E), reliable (C), depressed (N), lazy (C), or kind (A) now, *then* they tended to be ruder (A) later. In contrast, *if…* they were more outgoing (E), worried (N), and relaxed (N) now, *then* they tended to less rude (A) later. There were only two small self-feedback-loops for the lazy (C) and depressed (N) nodes. Both of these were the strongest self-feedback-loops in the lagged association network as well and indicate that feeling lazy (C) or depressed (N) had strong inertia – that is, *if…* the participant felt this way, *then* they were likely feeling similar at the next time point.

uSEM

Unified Structural Equation Modeling (uSEM) is another method for estimating partial contemporaneous and lagged relationships between indicators (Gates et al., 2010; Kim et al., 2007). Although its overall goal to estimate these contemporaneous and lagged associations is similar to graphicalVAR, it differs in a few key ways. First, rather than sequentially estimating a lagged and contemporaneous network, respectively, uSEM estimates these simultaneously. As a result, uSEM does not result in two p x p networks, one symmetric and one asymmetric. Instead, it results in a p x 2*p asymmetric matrix, which have been split up and visualized separately in Figure 3, for comparison with other methods. Second, rather than using regularization to penalize the regression coefficients, uSEM uses an iterative, automatic search procedure for retaining pathways in the model using Lagrange multiplier tests. Starting with an empty model, the procedure adds each indicator and tests the overall improvement in model fit according to the Lagrange multiplier tests. The variable that results in the largest jump in the test is included. Then the procedure is repeated with the remaining variables until there is no longer a significant jump in the Lagrange multiplier tests.

uSEM allows researchers to answer similar questions as graphical VAR and association networks. However, its implementation within the Group Iterative Multiple Model Estimation (GIMME) procedure also provides a unique opportunity for merging idiographic and group-level approaches and easy implementation in R using the gimme package (S. Lane et al., 2021). The GIMME procedure is a data-driven procedure for estimating both group-level and idiographic patterns of pathways in time series data (S. T. Lane et al., 2019). As currently implemented in the gimme package (S. T. Lane et al., 2016) in R, the procedure estimates a series of unified structural equation model (uSEM) for each person and constructs a group-level structure based on the individual-level models. It does not estimate a group-level matrix of point estimates. Instead it produces a group-level matrix of pathways that will be estimated for all individuals. uSEM uses an iterative procedure for retaining pathways in the individual models using Lagrange multiplier tests. The GIMME procedure begins by estimating the pathways to be retained at the group-level (i.e. in all individual-level models) by estimating individual-level models and retaining group-level pathways for those paths were shared by 75% of participants. Starting with a null model, pathways are iteratively added to the group-level structure (i.e. in all participants' final unique models) when the largest proportion of individuals (above a chosen threshold, 75% by default) show a better model fit according to the Lagrange multiplier tests. This procedure is continued until no additional pathways improve fit above the threshold. Idiographic models are then built using the uSEM procedure described above.

The difference between the glasso regularization used by graphical VAR and the stepwise Lagrange multiplier tests is important. Regularization retains or eliminates all pathways simultaneously by optimizing a fit criterion like eBIC or BIC (among others) and choosing the best-fitting model. In contrast, uSEM iteratively adds paths to the model that optimize Lagrange multiplier tests. Although these can produce almost identical results to regularized graphical VAR models, some longitudinal evidence suggests that graphical VAR models demonstrate somewhat better test-retest consistency than GIMME models in shorter time series (e.g., N ~ 50 assessments / person; Beck & Jackson, 2020, 2021). However, recent promising work has aimed to integrate regularization into the GIMME procedure in so-called hybrid GIMME (Luo et al., 2022). This procedure can now be readily implemented using the gimme package in R.

The uSEM models can be interpreted similarly to the graphical VAR models with two main exceptions. Although both the uSEM and graphical VAR models represent partial associations between indicators, uSEM coefficients are not correlations unless provided standardized data or if the coefficients themselves were standardized based on the residual covariance matrix. In addition, the contemporaneous associations are directed and simultaneously estimated with lagged associations, which results in directed contemporaneous associations. Although these are still interpreted as same time point associations, the goal is to better understand how changes in one may precede changes in the other. For example, the strong, negative association between reliable (C) and lazy (C) evidenced by the dark, thick dashed line between the two nodes, was evidence across each of the methods. However, in uSEM, this association is directed, such that feeling reliable (C) precedes feeling less lazy (C). Similarly, uSEM suggests that the positive association between worried (N) and depressed (N) is directional, such that feeling worried (N) precedes feeling depressed (N).

Using uSEM as part of the GIMME procedure, this participant's lagged network only contains self-feedback-loops. Each of the nine nodes has a self-feedback-loop. Of these, five are positive, suggesting self-perpetuating cycles. *If…* the participant felt worried (N), depressed (N), kind (A), reliable (C), of lazy (C) now, *then* they were likely to feel similarly later. They also had four negative self-feedback loops, suggesting negative reinforcement patterns. *If…* they felt relaxed (N), quiet (E), outgoing (E), or rude (A) now, *then* they were likely to feel less so later.

dynEGA

Finally, dynamic exploratory graph analysis (dynEGA) is a network-based approach that merges network science with dynamic systems theory through derivatives (H. Golino et al., 2022). Rather than examining levels of indicators co-occur (contemporaneous) or covary across fixed intervals (lagged), dynEGA examines the extent to which changes in levels of indicators covary over time. From a theoretical perspective, this has the advantage of more closely capturing how psychological phenomena change over time rather than just whether they tend to have similar levels at observed moments. More pragmatically, by using derivatives, they also overcome issues introduced by missing assessments when using fixed interval lags as in the previously described methods (see the section "Choosing a Network Model" below for a more thorough discussion).

In order to estimate these networks, the first step is to take the raw time series data of levels of indicators across time and transform them into derivatives using the generalized local linear approximation (GLLA; Boker et al., 2010; Deboeck et al., 2009). Using time delay embedding, first- (velocity) and second- (acceleration or changes in velocity) order derivatives are estimated using GLLA. Then, patterns of associations of derivatives among the derivatives are evaluated using exploratory graph analysis (H. F. Golino et al., 2020; H. F. Golino & Epskamp, 2017).

Like graphical VAR, dynEGA uses glasso regularization using eBIC for tuning parameter selection for the purposes of feature selection and to help prevent overfitting. But unlike both graphical VAR and uSEM, dynEGA also specifically focuses on understanding network topology as part of the model fitting procedure. dynEGA specifically uses community detection algorithms in order to understand how nodes cluster together, similar to how factor analytic approaches can be applied for dimension reduction of psychometric data (e.g., Golino et al., 2020). Although there are multiple available community detection algorithms available, both in general and as implemented in the EGAnet package in R, in the example participant in the bottom row of Figure 3, we opted for the Louvain community detection algorithm (Blondel et al., 2008). It has several advantages relative to other community detection algorithms, including its speed, its multilevel structure, and its overall performance (Gates et al., 2016).

Unlike association networks, graphical VAR, and GIMME, dynEGA does not produce both lagged and contemporaneous matrices of associations among indicators. Rather, both level and change are incorporated into a single matrix that captures partial correlations of change or the degree to which different indicators have similar velocity across the time series. As shown in the bottom row of Figure 3, the resulting symmetric matrix of associations can be visually represented similar to contemporaneous networks. The network shares many of the same edges as graphical VAR and uSEM, with many of the main differences being smaller (i.e. thinner and lighter) edges. As is clear in the figure, *if…* reliability (C) was decreasing, *then* laziness (C) also tended to be increasing and vice versa. In addition, *if…* laziness (C) was increasing, *then* relaxation (N) was also often increasing and rudeness (A) was sometimes decreasing. Indeed, one major difference between the graphical VAR network and the dynEGA network is the greater number of associations between changes in rudeness (A) with changes in other nodes. In graphical VAR, rudeness (A) was strongly predicted by previous time point levels of other indicators in the lagged network but was not associated with any indicators in the contemporaneous network. In contrast, in the dynEGA network, increases in rudeness (A) were weakly associated with increases in how outgoing (E) the participant was as well as how reliable (C) they felt as well as with decreases in laziness (C), as noted previously. This may be because dynEGA is incorporating both level and change into the associations, while graphical VAR attempts to separate these out by sequentially estimating lagged and contemporaneous associations, respectively.

dynEGA additionally emphasizes how the nodes cluster via community detection, in this case using Louvain. The Louvain algorithm identified three communities in this participant's experiences, with (1) rude (A), lazy (C), reliable(C), and depressed (N); (2) quiet (E), outgoing (E), and kind (A); and (3) relaxed (N) and worried (N) all falling into communities. This is notable because it suggests that the participant's experiences did not fall neatly into their putative Big Five domains. Instead, we learn that this participant's experiences of depression (N) and how rude (A) they are linked to how lazy (C) and reliable (C) they feel, while how kind (A) they are is more related to how quiet (E) and outgoing (E) they feel. In other words, the participant's more affiliative behaviors appear to be linked to how social they feel, while some emotions and behavioral responses are linked more to productivity.

Choosing a Network Model

In the previous section, we described four different network models that can be applied to time series data, such as those collected via active (e.g., EMA) or passive sensing (e.g., mobile sensing). None of these models are the “correct” choice under all conditions. Rather, each model has unique features and advantages under different conditions. Briefly, in this section, we will make a small number of recommendations to help guide the choice of a model on the basis of research questions, temporal properties of the data, and design considerations.

First, an important consideration when choosing a model is the structure of the data. Lagged methods, such as those used in lagged association networks, graphical VAR, and uSEM assume fixed intervals between assessments. If the intervals are not fixed, either due to a different sampling schedule (e.g., pseudo random, event contingent, etc.), late responses, missing responses, or overnight periods, the lags are agnostic to the different intervals between assessments. Such gaps can have two consequences. (1) The most common recommendation to deal with missing assessments is to add empty rows to the time series. Then, because lags are created by shifting the rows of the time series, missing values can multiply. Thus, even with relatively high adherence to sampling protocols, researchers could be left with less than 50% of usable observations when using lags. When missing periods are due to overnight periods and there are multiple assessments per day, another alternative is to use multilevel models in which observations can be nested within days to parse day variance from observation variance. However, this does not fully solve the issue when using lagged estimates without adding empty rows for overnight periods. Moreover, their application to the models described above can require more data due to the need to estimate parameters at both the observation and day level. (2) To the extent that the observed interval is critical in capturing contingent relationships, unequal intervals could greatly reduce both the sensitivity and specificity of the lagged model. Some more recently developed models, like continuous time VAR models (CT-VAR; de Haan-Rietdijk et al., 2017; Ryan et al., 2018), aim to deal with the limitations of assumptions of fixed interval lags, but the necessary data requirements (upwards of 100 assessments of each indicator) can sometimes be prohibitive, particularly when coupling less frequent active sensing with more frequent passive sensing. But dynEGA performs well even under these conditions, with time delayed GLLA showing good performance on short time series and regularization increasing the sparsity of the network as a whole (H. F. Golino et al., 2020; Hardt et al., 2020).

Second, the choice of model also depends on which aspects of a network are of interest. For example, in some cases, contemporaneous, concurrent associations alone may be of interest, making the estimation of lagged networks seem unnecessary. However, it is not possible to estimate only contemporaneous associations using either graphical VAR or uSEM. Rather, in both cases, both lagged and contemporaneous associations will always be estimated. In such cases, simply examining an association network of contemporaneous correlations may seem sufficient, coupled with follow-up examinations of the network topology via techniques like the Louvain community detection algorithm. However, examining contemporaneous associations alone ignores the autocorrelative structure of multivariate time series, which can confound and introduce bias into estimates of contemporaneous associations (McCleary et al., 1980). Thus, many recommend detrending the time series through differencing or residual-based regression approaches (Wang & Maxwell, 2015), which is similar to the residual-based approach used by graphical VAR's sequential estimation of lagged and contemporaneous associations (Wild et al., 2010). uSEM does so indirectly at best, which may not fully account for the trends in the data, so detrending preprocessing is recommended prior to analysis. Finally, dynEGA directly captures the autocorrelative structure of the data using time delay embedding and by examining associations of change (i.e. GLLA derivatives).

Given each of these, how do you choose a model? Our general recommendation is that no model should be taken as ground truth. Each should be examined across a range of tuning parameters, data cleaning choices, and modeling choices in order to better understand the robustness of the results. Similar to multiverse (Steegen et al., 2016) and specification curve analyses (Simonsohn et al., 2020), this recommendation suggests considering how differences across methods can bias our inferences when selecting a single model or specification of a model. Instead, by examining the impact of a range of choices, we can better understand the robustness and boundary conditions of the observed patterns, associations, and more. For example, the models presented in Figure 1 suggest that while the contemporaneous associations were quite consistently recovered across methods, the lagged associations differed greatly. This suggests that the lagged associations are likely unstable and should be interpreted with caution at best and disregarded completely at worst. These comparisons are also in line with the test-retest consistency of these models across one year (Beck & Jackson, 2020a) and the COVID-19 pandemic (Beck & Jackson, 2021e), which suggest much better consistency for contemporaneous associations than lagged associations.

Considering all of this together, we want to highlight that the goal of using these methods is to most aptly and accurately represent the research question at hand and the data available to test it. There will never be one “correct” model to apply to a set of data or to answer a research question, so researchers are left with the challenge of addressing theory-method match in each research endeavor and at each stage of each endeavor. Above we have aimed to demonstrate a series of models that can be used to estimate dynamic associations in multivariate time series data from active and passive mobile sensing. Furthermore, we linked these conditional and open systems frameworks of personality to demonstrate how interpreting the models in line with these helps to close the theory-method gap (G. W. Allport, 1960; Beck & Jackson, 2020a, 2020b; J. C. Wright & Mischel, 1987).

Personality as a Dynamic System

As demonstrated above, using network tools can help to close the theory-method gap by examining associations among features dynamically in ways that address questions raised by Allport, Cattell, and others. Below, we outline a few final considerations and possible additions to the dynamic network models reviewed in the previous section, most of which take advantage of a key passive sensor datapoint collected in almost all studies: date and time stamps. More broadly, in our view, mobile sensing data are ideal to expand and answer these questions because of the possibility of more frequent assessment.

Formal and Verbal Theories of Personality Dynamics

In 1957, Cattell noted the importance of incorporating time effects into models of personality. In addition to discussing of periodicity and cycles in psychological states, he argued that accounting for different time effects is important for creating reliable models from which conclusions can be drawn, writing that “the task of research is first to establish statistically and experimentally the nature of the rhythms and then to trace them to internal physiological or external environmental sources, or both” (Cattell, 1957, p. 610).

More colloquially, timing is an important dimension in understanding personality. When we consider the theories we have about the personalities of others, the frequency of, duration of, and change in experiences all play an important role in the ways in which we understand them. Colloquial phrases like “[They] are so often tired” (frequency), “[They] can get stuck in an anxious state for days” (duration), and “[They] can turn on a dime” (change), all highlight how time is an explicit part of how we understand and describe the personalities of others.

Thus, the methods appropriate for building personality theory require that the way that manifestations unfold over time, not just their momentary or aggregated levels, are incorporated. Although autocorrelations can help to capture persistence and dynEGA can help to capture rates of change, none of the previously reviewed methods are, at face value, able to deal with cyclical processes, time of day effects, and diurnal cycles. Below, however, we close our discussion of these methods by briefly reviewing evidence on such cycles in psychological phenomena and how they can be incorporated into dynamic network models.

Cycles in psychological processes

When describing the personality of others, another frequent description includes time of day effects. You might hear, for example, "Don't talk to [them] in the morning. [They]'ll chew your head off!" or "I tend to fade after lunch." Such descriptors signal possible diurnal cycles in psychological processes and phenomena. Indeed, accumulating evidence suggests not only that some psychological processes demonstrate reliable diurnal pattern (e.g., Broughton, 1975; Stone et al., 1996) across people but also that there are individual differences in such diurnal patterns that partially underlie broader individual differences. Some studies have tested how such cycles relate to broader between-person traits, such as higher circadian rhythm values (i.e. more pronounced 24-hour cycles) of phone usage being associated with Extraversion (Wang et al., 2018). Other studies have tested how passive mobile sensing indicators are associated with active mobile sensing indicators, such as personality states. One such study found that time of day was associated with Extraversion across people using both linear regression and machine learning prediction models (Rüegger et al., 2020).

Although such studies examining diurnal cycles and time of day effects of mobile sensing data are great steps forward, most such studies still search for group-level patterns or attempt to link the patterns to between-person personality traits. Many of these studies do not report variability of mobile sensing indicators either within- or across-people. Thus, there are many theoretically relevant open questions about how diurnal cycle and time of day effects can be used to better understand personality and other psychological phenomena, such as whether we can detect behavioral descriptors like "I tend to fade after lunch," how such patterns cluster together within and across people, and so on.

Quite simply, these diurnal and time of day effects can be included as nodes in the dynamic network methods reviewed in the previous sections (see Beck & Jackson, 2021 for example code on calculating each of the below). First, for example, a time of day node that is dummy coded as "morning," "midday," "afternoon,", "evening," and "night" could help address differences in each of the other nodes across the day. In other words, particularly when coupled with feature selection techniques, like glasso, any edges between these nodes and nodes from active or passive sensing indicate a time of day effect, partialling out all other relationships between other nodes – that is, a robust time of day effect for that indicator. Second, cosinor terms can be included, particularly when denser, passive sensing data are utilized. The most commonly used terms are both one and two period sine and cosine functions of decimal time (since midnight). Because these represent a more continuous but more complex method for addressing time of day effects, we recommend using these with careful planning and attention. Finally, trends can be included, such as linear, quadratic, and cubic trends across the time series. These are particularly important when the act of completing active or passive sensing is thought to potentially impact participants' behaviors and experiences. By including such trends across time, researchers can directly address questions about changes in the levels of the indicators across time as well as interpret associations among them adjusting for such trends.

Conclusion

Psychology is a dynamic science, yet much of the study of psychology relies on aggregating across dynamics of psychological phenomena and looking at individual differences or group-level differences of such aggregates, which creates a gap between psychological theories and the methods used to test them. In this paper, we discussed how dynamic passive and active mobile sensing data can be used to help close the gap. Using theoretical and empirical findings from the domain of personality psychology, we argued for both the importance of dynamics for studying and testing personality theory and for its utility in everyday life.

Our representation of both personality theory and dynamic methods was far from exhaustive. Rather, we hoped to demonstrate how theoretical propositions, both simple and complex, both narrow and sweeping, could be linked to dynamic methods better suited to testing the proposition than methods that rely on aggregates. In the simplest case, we argued that propositions that personality is a readiness for response (Allport, 1937) could be captured by looking at personality as rates of change of personality states. In a broader, more complex case, we highlighted how Allport's (1960) proposition that personality is an open system could be tested using dynamic systems approaches that build structural and mathematical models of dynamic features.

We believe that by bringing the theory-method gap in personality specifically and psychology more broadly to the fore, psychologists can make more active and informed choices in their model selection in ways that will better align theory and methods. By demonstrating a small number of dynamic models, we hope that readers of this chapter will consider how they may relate to theories in all disciplines of psychology. Moreover, we hope that much as we endeavored to start with a theory and then make the case for why different models test its proposition, that readers of this chapter will walk similar avenues and test old dynamic questions with new dynamic methods.

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