Modeling Dynamic Personality Theories in a Continuous-time Framework:
An Illustration

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Abstract

Personality psychology has traditionally focused on stable between-person differences. Yet, recent theoretical developments and empirical insights have led to a new conceptualization of personality as a dynamic system (e.g., Cybernetic Big Five Theory). Such dynamic systems comprise several components that need to be conceptually distinguished and mapped to a statistical model for estimation. In the current work, we illustrate how common components from these new dynamic personality theories may be implemented in a continuous-time modeling framework. As an empirical example, we use experience sampling data from $N = 180$ persons (with on average $T = 40$ [$SD = 8$] measurement occasions) to investigate four different effects between momentary happiness, momentary extraverted behavior, and the perception of a situation as social: (1) between-person effects, (2) contemporaneous effects, (3) autoregressive effects, and (4) cross-lagged effects. We highlight that these four effects must not necessarily point in the same direction, which is in line with assumptions from dynamic personality theories.

Keywords: *continuous-time modeling, between-person effects, contemporaneous effects, autoregressive effects, cross-lagged effects, personality dynamics, experience sampling*

Modeling Dynamic Personality Theories in a Continuous-time Framework: An Illustration

Ever since the conclusion of the person-situation-debate, new theories of personality conceptualize personality as dynamic (Baumert et al., 2017; Danvers, Wundrack, & Mehl, 2020; DeYoung, 2015; Quirin et al., 2020; Revelle & Condon, 2015; Sosnowska, Kuppens, De Fruyt, & Hofmans, 2020). Dynamic personality theories incorporate two important insights from the person-situation-debate (Fleeson & Nofle, 2009): First, personality traits are stable entities that allow describing how a person thinks, acts, or feels in general (Funder, 2001; Roberts & DelVecchio, 2000; Roberts & Yoon, 2021). Stable personality traits allow describing inter-individual differences and can predict important inter-individual differences in life-outcomes such as longevity, well-being, or career success (e.g., Ozer & Benet-Martínez, 2006; Roberts, Kuncel, Shiner, Caspi, & Goldberg, 2007; Soto, 2019). Second, dynamic personality theories incorporate variability as an aspect of personality. A person behaves differently in different situations (Baird, Le, & Lucas, 2006; Fleeson, 2001; Mischel & Shoda, 1995) and even differently in similar situations (Horstmann, Rauthmann, Sherman, & Ziegler, 2021a); further, similar persons behave differently in similar situations. Momentary manifestations of personality in specific situations are called personality states (Baumert et al., 2017; Horstmann & Ziegler, 2020). In the long-term, experiencing a variety of personality states in daily life can lead to changes in personality traits (Quintus, Egloff, & Wrzus, under review; Wrzus & Roberts, 2017). Dynamic personality theories thus, implicitly or explicitly, build a bridge between seemingly contrasting positions, namely the stability of traits, variability of states, and malleability of personality traits in the long term. Despite the recent efforts of proposing dynamic personality theories (DeYoung, 2015; Fleeson & Jayawickreme, 2015; Jayawickreme, Zachry, & Fleeson, 2019; Mischel & Shoda, 1995; Quirin et al., 2020; Tett & Guterman, 2000; Tett, Toich, & Ozkum, 2021), empirical examinations of dynamic theories, including several variables measured and examined together across time are scarce (Danvers et al., 2020; Sosnowska et al., 2020). In the current study, we illustrate how dynamic personality theories could be modeled in a continuous time framework, examining the

interplay between three theoretically relevant domains (DeYoung, 2015; Horstmann, Rauthmann, Sherman, & Ziegler, 2021b): situation perception, affect, and behavior.

Dynamic Personality Theories

The person-situation-debate was fought over the question how behavior can best be predicted; either with personality traits or with situational factors (Mischel, 1968, 2009). The debate started following findings that momentary behavior (or, more general, personality states) cannot be well predicted with global personality traits and that instead situational forces may best be used to explain momentary behavior (e.g., Hunt, 1965; Mischel, 1968). As is often the case, more nuanced perspectives emerged as a result of the debate. Average tendencies in behavior and long-term consequences can be well predicted with personality traits (Epstein, 1979, 1983; Soto, 2019), and momentary instantiations of behavior can be well predicted with situational factors (e.g., Fleeson, 2001; Horstmann et al., 2021b; Mischel & Shoda, 1995; Roemer, Horstmann, & Ziegler, 2020; Sherman, Rauthmann, Brown, Serfass, & Jones, 2015). This evidence has led to a "synthetic resolution" (Fleeson & Nofle, 2009) of the person-situation debate (for an overview, see Jayawickreme, Fleeson, Beck, Baumert, & Adler, 2021). Theories of personality must contain stable (trait) and variable (state) aspects of personality. These theories allow, on the one hand, for describing people in general terms (e.g., as extraverts), but also explain how momentary behavior manifests in daily life. There are numerous personality theories that could be reviewed at this stage, but we focus on five different personality theories and how they incorporate stable and variable aspects of personality: Three representing somewhat earlier theories: Cognitive Affective Personality System (CAPS; Eaton, South, & Krueger, 2009; Mischel & Shoda, 1995), Trait Activation Theory (TAT; Tett & Burnett, 2003; Tett & Guterman, 2000; Tett et al., 2021), and Whole Trait Theory (WTT; Fleeson, 2001; Fleeson & Jayawickreme, 2015); and two rather recent ones, Cybernetic Big Five Theory (CBFT; DeYoung, 2015) and the Cues-Tendency-Action model (CTA; Revelle & Condon, 2015). All theories have in common that they require modelling several

variables simultaneously, and stable intra- and inter-individual patterns of thoughts, feelings, and behavior.

The CAPS model states that consistent patterns in behavior are a result of cognitive processing units. A person behaves consistently according to their idiosyncratic interpretation of the world around them (Mischel & Shoda, 1995). This leads to characteristic *if...then* patterns; if in situation A, then behavior B. According to CAPS, personality represents interindividual differences in these specific *if...then*-patterns (Jayawickreme et al., 2021). This theory therefore highlights the importance of situational appraisal and affect as an antecedent of situational behavior. Furthermore, *if...then*-contingencies can vary between persons; that is, the relation among the variables in the system is itself an interindividual difference.

TAT states that personality traits are "activated" in certain situations, and that only specific situations allow for the manifestation of personality traits. TAT requires that certain situational features are present (e.g., people around oneself) in order for a trait to manifest (e.g., extraverted behavior). Once a trait relevant situation arises, it allows differentiating who does and who doesn't score high on a trait. Similar to CAPS, TAT therefore requires that situational features trigger behavior, and that behavior is displayed in situations.

Building mainly on the CAPS framework, WTT has explicitly differentiated between two central elements of personality (Fleeson, 2001; Fleeson & Jayawickreme, 2015; Jayawickreme et al., 2019). A (1) descriptive part and (2) an explanatory part. First, personality traits are conceptualized as density-distributions of behavior, and people differ – descriptively – in their unique density distributions (Fleeson, 2001; Wilson, Thompson, & Vazire, 2017). These distributions are stable over time (Fleeson & Gallagher, 2009; Jones, Brown, Serfass, & Sherman, 2017). Their central tendency (e.g., the average) indicates the propensity of a person to manifest a certain behavior. Momentary behavior is, in the explanatory part of the theory, a reaction to and an action in situations, similar to the CAPS framework. Again, this theory also highlights the fact that

people possess stable inter-individual differences, but that these differences can variably manifest in different situations.

CAPS, TAT, and WTT are broader theories that suggest that persons and situations interact to produce momentary behavior. All of the theories (and others, see Jayawickreme et al., 2021) acknowledge that persons have stable traits that somehow manifest in daily life. Yet these theories do not explicitly consider how a person goes from one situation to another and how a person decides (consciously or unconsciously) which behavior to manifest in which situation. This requires that (a) time is considered explicitly, and (b) that people can learn through some form of feedback from their past behavioral experiences.

CBFT and CTA are two frameworks that extend earlier dynamic theories in this regard. In CTA, Revelle and colleagues (Revelle & Condon, 2015; Revelle & Wilt, 2021) suggest that "traits can be seen as [interindividual differences in] rates of change in states in response to environmental cues" (p. 70). Here, an extraverted person would then act extraverted if at least minimal social cues were present (as social cues are assumed to trigger extraverted behavior). Generally speaking, a situational cue will be perceived by a person and, depending on their tendency to (re)act to or in line with this cue, this person will show a specific action. Two features of this theory are worth highlighting with respect to the previously presented theories. First, depending on the evaluation of an action, a person is able to learn something. In the CTA model, this means that the stimulation a cue exerts on the tendency to act is changed (e.g., if my friends call me (i.e., a social cue) to go out with them (i.e., show extraverted behavior), this will also depend on my previous experiences (e.g., if I had a good time last time, I might go, otherwise, I might choose not to go)). Additionally, the action also satisfies (or, in dynamic systems, consummates) the tendency to act; after showing a certain behavior, the short-term tendency to show this behavior decreases. This means that the effect of a situational cue on behavior—and vice versa—changes over time (e.g., directly after the call, one may have a strong urgency to go out, several hours and social interactions later, this urgency might have decreased). Importantly, such

changes are a function of the past and the time that passes, a core feature of a dynamic model. The second important point of dynamic personality theories is that different actions inhibit each other (e.g., I can only write this article *or* go out with my friends, both at the same time is not possible) which means that, ideally, several processes (or variables) and their interplay should be considered in the examination of dynamic personality theories.

Finally, CBFT (DeYoung, 2015) also conceptualizes traits as tendencies to act (similar to CTA) or as probabilities to be in a certain state (similar to WTT) and also describes personality as a sequence of actions. CBFT extends the explanatory part of WTT by stating that people tend to gravitate to a certain trait-relevant behavior. The behavior persons naturally gravitate to is then considered their personality trait. Similar to CTA, a goal is activated (e.g., by a situational cue), an action is selected, the action is performed (e.g., the behavior), and then the outcome of that action is interpreted and evaluated, providing feedback for future actions. The evaluation of a certain action, can, for example be performed based on the positive affect that has resulted based on the action (e.g., following an invitation to party and having lots of fun will increase the probability of going out the next time one is invited).

Several articles have implemented models for the examination of dynamic personality theories, the most recent ones by Sosnowska et al. and Danvers et al. (Danvers et al., 2020; Sosnowska et al., 2020). Sosnowska and colleagues used a Bayesian hierarchical Ornstein-Uhlenbeck model (BHOUM), while Danvers and colleagues tested a Change as Outcome model (COM). Both models have the advantage that they explicitly consider time as a relevant variable; and in both applications, the within-person change of one variable over time was modeled. However, neither article considered more than one variable simultaneously, as would explicitly be required by the dynamic personality theories described earlier.

Closely building upon this recent work, we believe that these shortcomings can be overcome by a more general approach to continuous time modeling. Continuous-time modeling has recently found its way into social science and behavioral research (e.g., van Montfort et al.,

2018) and usage of continuous-time models is accelerating, presumably because continuous-time modeling offers some attractive advantages. In short (see, e.g., Hecht et al., 2019; Hecht & Zitzmann, 2021b; Voelkle & Oud, 2013), continuous-time modeling offers to easily integrate data from flexible longitudinal designs with unequal and individual spacing between measurement occasions, facilitates cross-study comparisons and helps with exploring the unfolding of dynamic effects. Continuous-time modeling is therefore one suitable and promising framework for modeling the propositions and elements outlined in dynamic personality theories.

Purpose and Scope

In the present article, we illustrate how dynamic personality theories could be modeled in a continuous-time framework. The article is organized as follows: First, we describe the components of continuous-time models and how they map onto components of dynamic personality theories. Second, as an empirical illustration, we apply continuous-time modeling to explore the dynamics between sociality, happiness, and extraversion as suggested by DeYoung (2015). Third, we conclude with a discussion and future directions of implementing dynamic personality theories.

Modeling Dynamic Personality Theories in a Continuous-time Modeling Framework

As elaborated in the introduction, dynamic personality theories comprise several components. In this section, we conceptually describe these components and map them to parameters of the continuous-time model. For ease of reading, we refrain from presenting equations and technical details of the employed continuous-time model; these are provided in the Supplementary Material for the more technically oriented reader. The four discussed components are (1) between-person effects, (2) contemporaneous effects, (3) autoregressive effects, and (4) cross-lagged effects. *Figure 1* illustrates these four components, respectively, for the three exemplary self-reported variables situation perception, affect, and behavior, which are usually central ingredients of dynamic personality theories (DeYoung, 2015; Quirin et al., 2020; Wilt & Revelle, 2015).

Between-person Effects

Historically, personality psychology and psychological assessment were concerned with the description, assessment, and explanation of inter-individual differences, that is, characteristics that allow differentiating one person from another (Baumert et al., 2017; Quirin et al., 2020). These differences once assessed can then be used to predict important inter-individual differences, such as career success (e.g., Barrick & Mount, 1991; Salgado, 1997). Following these initial efforts, substantial proportions of the literature on psychological assessment and personality psychology focus(ed) on the between-person level, reflecting theoretical assumptions of personality psychology.

Thus, in models for dynamic personality theories, there needs to be a component that reflects an individual average level consistent across—at least—the time span investigated. Any person therefore has a value on these variables, to which one could refer as their trait score (Danvers et al., 2020; Fleeson, 2001; Sosnowska et al., 2020), or an individual “process mean”. Curran and Bauer (2011) already discussed how such “between-person effects” can be disentangled from within-person effects in longitudinal models. In our continuous-time model (see Supplementary Materials for equations and technical details), the individual process means, contained the vector $\mu_{j\infty}$ are assumed normally distributed with the average process means (μ_{∞}) and a between-person process mean covariance matrix (Σ_{∞}). On the diagonal of this matrix, we find the variances of the process means, for example, the stable between-person variance of state extraversion across time. The off-diagonal then contains the covariances of the between-person characteristics. *Figure 1* (Panel A) illustrates this component. The continuous-time model implemented here provides us with variances and covariances of time-stable affect, behavior, and situation perception. These can be interpreted as the association of average tendencies to perceive a situation as social, the average affect, and the average extraverted behavior across the study period.

Contemporaneous Effects

Importantly, when looking at two or more variables, their relation can be different at different levels. Two personality traits can for example be positively associated at the between-person level. Yet, at the within-person level, their relation can be negative (e.g., Horstmann & Ziegler, 2020). Hamaker (2012) illustrated this with the relation between typing speed and typing accuracy: Those who type faster are generally those who make less errors (between-person level). Yet, if an individual person types faster, they will make more errors (within-person level). Typing speed and typing accuracy are therefore positively related at the between-person level, but negatively related at the within-person level. The same can be true for personality traits and their manifestations. Positive and negative affect, for example, are generally considered to be uncorrelated at the between-person level (Watson & Tellegen, 1985). On average, that is, at the between-person level, those experiencing high positive affect can also experience high negative affect but also low negative affect. Yet, it is very difficult if not impossible to experience positive and negative affect at the same time, in the same moment (Dejonckheere et al., 2019). The relation that is established at the between-person level therefore may not generalize to the within-person level and vice versa (a phenomenon that is often discussed under the label “ergodicity”, e.g., Adolf & Fried, 2019; Brose et al., 2015; Voelkle et al., 2014). In the continuous time framework, the average within-person variances and associations of variables for any specific point in time are characterized by the entries in the *within-person covariance matrix* ($\mathbf{Q}_{\infty}$), which is assumed equal for all individuals and time points. The covariances of states are then on the off-diagonal of the same matrix. Such a covariance for example indicates that higher state extraversion is associated with higher state happiness. *Figure 1* (Panel B) illustrates this component.

Autoregressive Effects

Dynamic models of personality theory also assume that characteristics change across time. This change is not merely random fluctuation, but the states that people exhibit across time are dependent to a certain extent. Certainly, a good predictor for any momentary instantiation of behavior, thoughts, and feelings is the behavior, thought, or feeling shown in the previous occasion. In other words, if a person types slowly today, they are also likely to rather type slowly tomorrow. In our model, this is reflected by autoregressive effects (*Figure 1 Panel B*). These autoregressive effects indicate how rigid or persistent a process is. If the autoregressive effect is high, this means that the current state is—on average—highly associated with, that is, well predicted by, the previous state, conditional on all other effects modeled. Contrarily, a low autoregressive effect indicates that the previous state has low predictive impact for the next state. In light of dynamic personality theories, an autoregressive effect could be interpreted as how quickly a person returns to her or his equilibrium after a deviation from the mean. A high autoregressive effect would then indicate a slow return to the mean level (i.e., equilibrium), whereas a low autoregressive effect would indicate a fast reversion. Furthermore, in the continuous-time framework, autoregressive effects are also dynamic. This means that the effect of any previous behavior, thought, or feeling on later behavior, thoughts, or feelings becomes stronger or weaker after a certain time—or first stronger, then weaker. Instead of assuming that the effect remains stable for any period of time, the continuous time framework assumes that the estimate of the effect depends on the time span between the measurements.

Cross-lagged effects

When examining short-term or long-term processes across time, it is important to note that a relation between two variables as established at the within-person level (e.g., positive and negative affect are negatively correlated within an individual) may no longer hold at the between-person perspective. This is similar to the paradox described earlier. Two variables,

for example, could be negatively associated within the same occasion, but positively associated at the within-person level, across time. Consider, for example, extraversion and functional health. Someone who has very low, momentary functional health, is likely to be low in momentary extraversion (e.g., lying sick in bed does not call for meeting friends). However, across time, these variables were shown to be associated positively. Those who have higher extraversion have higher functional health later in time, and vice versa (Müller et al., 2019).

This example illustrates that if one is interested in the question how one state is related to a later state of another domain, it requires assessing different states of the same (at least one) person over multiple situations. Here, one could then estimate the lagged state–state association. We will refer to associations between different states across time as cross-lagged effects. Our continuous-time model provides such cross-effects in the off-diagonals of the autoregressive matrix ($\mathbf{A}_{\Delta t(p-1)}^*$).

Figure 1 Panel D illustrates this component of dynamic personality theories.

Empirical Illustration

For our illustration, we will use a continuous-time model to examine (1) between-person effects, (2) contemporaneous effects, (3) autoregressive effects, and (4) cross-lagged effects. Theoretical considerations and definitions of the examined constructs are less relevant for the intended illustration purpose, but are provided in the Supplementary Material. In short, the three variables under consideration are Sociality, Happiness, and Extraversion, which are examples of the general phenomena Situation perception, Affect, and Behavior used for the general illustrations above. It has been shown that all three variables—sociality, happiness, and extraversion are positively associated at the between-person level (between-person effects) and positively associated at the within-person level (contemporaneous effects) (Horstmann et al., 2021; Kritzler et al., 2020). However, the dynamic association of these three variables (autoregressive and cross-lagged effects) have not been examined in unison in a single model, although empirical

investigations between at least two of these constructs exist (e.g., Elmer, 2021; McCabe & Fleeson, 2016; Quoidbach, Taquet, Deseilles, de Montjoye, & Gross, 2019; Rauthmann, Jones, & Sherman, 2016). In this empirical example of modeling dynamic personality theories, we furthermore illustrate two important aspects: First, the fact that an association between two or more variables can be different depending on the kind of relation that is examined (see earlier, components 1–4 of dynamic personality theories and continuous-time models). Second, that the time interval that is examined plays an important role for the examination and interpretation of cross-lagged and autoregressive effects. Throughout this empirical example, we use “S” (Situation) as an abbreviation for Sociality, “A” (Affect) for Happiness, and “B” (Behavior) for Extraversion.

Data and Procedure

The data set that we use in the current article has been analyzed in several previous articles before (Horstmann et al., 2021b, 2021a; Rauthmann et al., 2016; Sherman et al., 2015). However, the analyses reported here have—to our best knowledge—not been conducted before. The data collection procedure is extensively described in Sherman et al. (2015). Sherman and colleagues used an experience sampling design with repeated assessments throughout the day, assessing personality states, situation perception, and state happiness. In addition, they also collected self-reports of global trait variables (e.g., demographics and personality traits). However, these variables are not analyzed in the current study. A full description of the data frame and detailed information about the study is available in Sherman et al. (2015).

The exact sampling schedule can be found in the online supplemental material of Sherman et al. (2015). In short, participants were invited to participate in the experience sampling part of the study via SMS. Participants received eight invitations per day at randomly selected time points between 9 a.m. and 11 p.m., although it was made sure that

invitations were always at least one hour apart. For each specific day of the study, all participants received their invitations at the exact same time.

Measures

In an initial lab session, participants reported their age, gender, and ethnicity. In the experience sampling section of the study, participants were then asked to report their state extraversion, their state sociality, and their state happiness.

State sociality. State sociality describes how social a person perceives a situation. State sociality thus reflects characteristics of the current situation (Rauthmann, 2015; Rauthmann et al., 2014). Assessing situational characteristics instead of situational cues is a valid way of gauging the influence of momentary situations (Horstmann & Ziegler, 2016; Parrigon, Woo, Tay, & Wang, 2017; Rauthmann, Sherman, & Funder, 2015). State sociality was assessed using the S8-I (Rauthmann & Sherman, 2016b). The S8-I assesses the Situational Eight DIAMONDS. The DIAMONDS are eight situation dimensions on which psychological characteristics of situations can be rated. To assess state sociality, participants were asked how well the statement “Social interaction is possible or required.” described their current situation. Responses were given on a 7-point rating scale with 1 = “extremely uncharacteristic” and 7 = “extremely characteristic”.

State extraversion. State extraversion describes how outgoing and sociable a person behaves in the moment. State extraversion was assessed by asking participants about their current behaviors and feelings on one item, using a 7-point bipolar rating scale. The item assessing extraversion was “outgoing, sociable—reserved, quiet”. The scores were recoded such that higher values represent higher state extraversion.

State happiness. State happiness describes how happy a person is at the current moment. State happiness was assessed similar to state extraversion. Participants reported how

they currently felt on a 7-point bipolar rating scale, with the end-points “happy, positive—sad, negative”. The scale was recoded such that higher values represent higher state happiness.

Data Preparation

We screened Sherman and colleagues’ data of 210 persons by investigating individual “spaghetti plots” (i.e., values of raw data for each variable plotted against time points). Before running our model, 30 persons with potentially problematic data (e.g., bottom/ceiling responses, zero or minimal variance in responses, too few responses) were excluded to potentially facilitate model convergence, resulting in a sample size of $n = 180$ persons for our analyses. Spaghetti plots of included and excluded persons are provided in the Supplemental Material.

Descriptive Statistics

The number of time points per person ranged from 8 to 55 ($M_{T_j} = 40.11$, $SD_{T_j} = 8.40$). The total number of observations was 7,220. The mean time interval length between consecutive time points is $M_{\Delta} = 3.80$ h ($SD_{\Delta} = 4.72$). Figure S1 in the Supplemental Materials shows the distribution of lengths of time intervals between consecutive time points. The mean of the individual means (over time points) is $M_S = 4.02$ ($SD_S = 0.91$) for Situation, $M_A = 5.21$ ($SD_A = 1.01$) for Affect, and $M_B = 4.51$ ($SD_B = 0.96$) for Behavior. The average of descriptive within-person standard deviations is $M_{SD,S} = 2.07$ ($SD_{SD,S} = 0.49$) for Situation, $M_{SD,A} = 1.39$ ($SD_{SD,A} = 0.43$) for Affect, and $M_{SD,B} = 1.65$ ($SD_{SD,B} = 0.48$) for Behavior.

Model

We adapted the continuous-time model formulation and notation from Hecht and Zitzmann (2020, 2021a) and Hecht et al. (2019), which is based on the works of Oud and Delsing (2010) and Voelkle et al. (2012). The model formulation, the calculation of further statistics, and a brief description of the presented plots is provided in the Supplemental Material.

Analysis

We ran the continuous-time model using R 4.0.3 (R Core Team, 2020) and the R package ctsemOMX (Driver, Oud, & Voelkle, 2020), which offers frequentist estimation of continuous-time models by interfacing to the R package OpenMx (Boker et al., 2020), with the NPSOL optimizer and a convergence criteria of 10^{-6} . Run time was 3 h 29 m on one Intel Xeon Gold 5120 (2.20GHz) CPU of a 64-bit Linux Debian 10 “Buster” computer. The model¹ cleanly converged (OpenMx exit code=0) at a deviance of 82,737.37. The deviance change plot (Figure S2 in the Supplemental Material) revealed no abnormalities. To improve trust in the estimation results, we ran the model with two other optimizers (CSOLNP, SLSQP) and different starting values resulting in comparable estimates.

Results

The estimates of the model parameters are shown in Table S1 (in the Supplemental Material). The process means for the three variables S, A, and B are 3.79, 5.46, and 4.90, respectively. Persons vary in their individual means with variances 0.54, 0.72, and 0.33. The within-person variances for S, A, and B are 2.41, 1.58, and 1.96. Note that these are different from the descriptive variances, as we estimate all effects (between-person effects, autoregressive effects, cross-lagged effects, contemporaneous effects) simultaneously. Measurement error variances are 2.31, 0.74, and 1.53, respectively. Concerning the first time point parameters, we observe some differences. The means at the first time point deviate from the process means with 0.89, -0.71, and -0.51. The within-person variances at the first time point are roughly similar to the within-person variances of the processes for variables S ($\sigma_{fWS}^2 = 2.50$ vs. $\sigma_{wS}^2 = 2.41$) and B ($\sigma_{fWB}^2 = 2.22$ vs. $\sigma_{wB}^2 = 1.96$), whereas a more pronounced difference prevails for variable A ($\sigma_{fWA}^2 = 3.11$ vs. $\sigma_{wA}^2 = 1.58$). The eigenvalues of the drift matrix A (-2.13, -1.88, and -0.03) are all below 0 indicating that the matrix is negative definite which, inter alia, implies invertibility. In Table S2 (in the Supplemental Material),

¹ For estimation purposes a time interval of 4h was chosen. Some results are reported in hours.

reliability and intra-class correlation coefficients are presented. Reliability ranges from 0.56 (variable S), over 0.60 (B), to 0.76 (A). The ICCs were estimated to 0.18 (S), 0.31 (A), and 0.15 (B). Thus, 18% / 31% / 15% of the (measurement error free) variance is related to between-person differences.

Between-person Effects

The between-person process mean covariances are also given in Table S1. For better interpretability, these covariances were transformed to correlations: $r_{\mu AS} = 0.37$, $r_{\mu BS} = 0.88$, and $r_{\mu BA} = 0.50$. Thus, the correlational relation between trait affect (happiness) and trait situation (sociality) is moderate, between trait behavior (extraversion) and trait situation very large, and between trait behavior and trait affect large. Being generally more happy is moderately associated with generally perceiving situations as more sociable. Generally behaving more extraverted is very highly associated with perceiving situations as more sociable. Exhibiting generally more extraverted behavior is highly associated with generally being more happy.

Contemporaneous Effects

The correlations based on the within-person covariances (Table S1) are: $r_{wAS} = 0.18$, $r_{wBS} = 0.49$, and $r_{wBA} = 0.81$. Thus, the correlational relation between state affect (happiness) and state situation (sociality) is rather small, between state behavior (extraversion) and state situation large, and between state behavior and state affect very large. Momentarily being more happy is somewhat associated with perceiving the current situation as more sociable. Engaging in more extraverted behavior is highly associated with perceiving the current situation as more sociable. Momentary extraverted behavior is very highly associated with being more happy at that moment.

Autoregressive Effects

The autoregressive effects and their dependency on the time interval are shown in the upper panel of *Figure 2*. For a time interval of 0, the autoregressive effect is always 1 per definition as no time has passed. For longer time intervals the autoregressive effects change and for $T \rightarrow \infty$ they will converge to 0 as two states lose their associations. For Situation, we see that the autoregressive effect drops rapidly with increasing time interval length. This means that the perception of a situation as social is persistent for temporally close time points (up to a few hours); for more distant time points, state values of perceiving a situation as social are only loosely associated. For happiness, we see a reversed sign in the autoregressive effect after a few hours. For time interval lengths up to roughly 2 hours, happiness states are positively associated meaning that a deviation from the mean at one time point predicts a positive deviation at a later time point, and, vice versa, a negative deviation now predicts a negative deviation later on. For time intervals greater than roughly 2 hours, the negative sign of the autoregressive effects indicates that positive deviations predict negative deviations and, vice versa, negative deviations predict positive deviations. Behavior is the most persistent of our three investigated variables; the autoregressive is around 1 and just very slowly declines for increasing time intervals. This means that extraverted behavior is very stable. For instance, if a person shows highly extraverted behavior at a time point, it is highly likely that the behavior is highly extraverted a couple of (or even many) hours later. In summary, by evaluating the graphical display of the autoregressive effects depending on the length of the time interval, we can derive interesting insights on how temporally persistent state values of variables are. The same evaluation of parameter dependency on time interval length can be conducted for cross-lagged effects. These effects, as presented here, are controlled for the other included effects.

Cross-lagged Effects

The dependency of the standardized cross-lagged effects on the time interval length are shown in the lower panel of *Figure 2*. This figure nicely illustrates how each of the six cross-lagged effects in our study depends on the time interval length in hours (x-axis). For an interval length of zero, the cross-lagged effects are zero; for increasing interval length, they increase until a peak value is reached and then start to decrease. The peak values and their corresponding interval length are given in Table 1. We exemplarily pick one of the cross-lagged effects (Situation Perception $\rightarrow$ Affect) for interpretation. We can see that this cross-lagged effect is zero for a zero interval length. Then for increasing interval length its value increases in size with a negative sign until it reaches its peak. After that peak value, the cross-lagged effect size diminishes slowly with increasing time between time points. We could arbitrarily choose any time interval length for interpretation, but we think that researchers often are interested in the maximum effect of one variable on another. Hence, we interpret the peak standardized cross-lagged effect which is $a_{\text{peak,std,S} \rightarrow \text{A}}^* = -0.39$ at the time interval $\Delta_{\text{peak,S} \rightarrow \text{A}} = 9.48$ h. As we standardized the cross-lagged effects with respect to the within-person standard deviations (see Equation 13 in the Supplementary Material), the effects are expressed in *SD*. The within-person variances (which can be transformed into *SD* by taking the square root) are presented in Table S1 in the Supplementary Material). For Situation Perception, the within-person standard deviation is $SD_{\text{wS}} = \sqrt{2.41} = 1.55$ and the within-person standard deviation for Affect is $SD_{\text{wA}} = \sqrt{1.58} = 1.26$. The interpretation of the cross-lagged effect from Situation Perception on Affect is then: A one *SD* increase in the variable Situation Perception (i.e., an increase of $1 \cdot SD_{\text{wS}} = 1.55$) is associated with a decrease of -0.39 *SD* in Affect (i.e., a decrease of $-0.39 \cdot 1.26 = -0.49$) 9.48 h later. The values for the other cross-lagged effects can be interpreted analogously.

Whereas *Figure 2* shows the dependency of model parameters (autoregressive and cross-lagged effects) on the time interval length, we could ask ourselves how the system itself—that is, the state values of all variables—evolves over time when the state of one variable is altered (what could be labeled as an *impulse*). Such system behavior is best explored in *impulse response plots*

(Figure 3). Impulse response plots show how an impulse (i.e., a certain state value) on one variable affects the system (i.e., all variables). If, for example, a person perceives a situation as very social, how will this affect the course of extraverted behavior and happy and also sociality itself? In the upper plot, the progression of the system (i.e., all three variables) is displayed when variable Situation is 1 *SD* above its mean at the first time point and thus asserts effects on Affect and Behavior. The middle and lower plot show the progression of the system for an impulse of 1 *SD* in Affect and Behavior, respectively. The plots can be interpreted as follows: Perceiving the situation as more sociable is associated with less happiness and less extraverted behavior later on. The reduced happiness and sociable behavior go along with increased perception of the situation as sociable for the next couple of hours. Being more happy is associated with later perceiving the situation as more sociable and with less later extraverted behavior. Engaging in more extraverted behavior is associated with pronounced happiness and perception of the situation as less sociable later on. Note, that these interpretations are conditional on any between-person associations and contemporaneous effects as discussed above. In all plots, one might identify a general trend: Affect and Behavior evolve rather synchronously, whereas the trajectory of Situation is mirror-inverted to Affect and Behavior. That is, lower happiness and lower extraverted behavior go along with higher sociable situation perception, and vice versa, when the situation is perceived as less sociable, then happiness and extraverted behavior are higher.

Discussion

Recent theoretical advances in personality psychology propose that personality can best be understood as a dynamic system (Danvers et al., 2020; DeYoung, 2015; Quirin et al., 2020; Sosnowska et al., 2020). There are a number of ways how such a dynamic system can be modelled. Here we presented an implementation of a continuous time model that allows simultaneously estimating between-person effects, contemporaneous effects, autoregressive effects, and cross-lagged effects for three different, theoretically interconnected variables.

In our exemplary analysis of the association of sociality, happiness, and extraversion, all three variables were positively associated at the between-person level. Furthermore, all contemporaneous effects were positive. The effects reported here resemble those (at least in their direction) published earlier (Horstmann et al., 2021b; e.g., Horstmann & Ziegler, 2019; McCabe & Fleeson, 2016; Sherman et al., 2015). Furthermore, they also fit theoretical assumptions about the positive associations of sociality, happiness, and extraversion.

Yet, psychology is oftentimes concerned with the prediction of outcomes, that is, telling what will happen in the future, at the individual level. First, we examined autoregressive effects. The autoregressive effects of extraversion and sociality were and remained positive, indicating stability. Furthermore, extraversion was more stable compared to sociality. However, the autoregressive effect of happiness was first positive and then, later on, negative. This means that experiencing happiness now is related to experiencing more happiness later, however, after about 2-3 hours, this effect was reversed in the current data. Experiencing more happiness now was then related to experiencing less happiness later. These results are in line with previous findings, reporting that behavioral variables are more stable compared to affective variables (Podsakoff, Spoelma, Chawla, & Gabriel, 2019). However, we concede that it is practically impossible to predict these exact patterns based on the current knowledge about personality dynamics.

Second, we examined the cross-temporal associations of different variables. If a person goes to a party and acts extraverted, will this be associated with more or less happiness later? Our results show that research that has examined between-person effects or even contemporaneous effects cannot be consulted to answer such questions. Four of the six cross-lagged effects examined were negative: High state sociality was associated with reduced state happiness at a later point in time, but higher state happiness was associated with increased state sociality later in time. Perceiving a situation higher on sociality was related to lower state

extraversion later in time, and state extraversion was related to lower state sociality later in time. Finally, state extraversion was related to higher state happiness, but higher state happiness was related to lower state extraversion later in time. For example—but speculatively—a person finding themselves in a social situation might, during this situation, display high levels of extraversion and experience high state affect (contemporaneous effects). After some time, however, this will be associated with lower state happiness, and lower state extraversion, as indicated by the negative cross-lagged effects. High state extraversion, however, is associated with perceiving a later situation lower on sociality, but it will be associated with higher state happiness. As this example already shows, the pattern of associations is highly complex, especially if all these effects occur simultaneously in daily life. It has to be noted, though, that the peak of these effects occurred comparatively late (e.g., the effect of sociality on happiness took 9.48 h to unfold). This has to be understood as an average effect, which is the best estimate across the study, but may not necessarily apply to all hours of the day. Such effects specific to the time of the day could be added in a future extension of the continuous-time model presented here. However, current implementations of dynamic personality theories do not make any predictions about when an effect should unfold. The results presented here can guide such future refinements.

As Hamaker (2012) noted, researchers should start thinking “within-person” (see also Molenaar, 2004). The current results support this plea, but add an example for even another perspective and extension of this paradigm. Within-person cross-lagged effects can be different from contemporaneous effects. This has important implications. We would argue that most persons take exactly this perspective when thinking about how human behavior unfolds. When asking someone “why are you so happy?”, their usual response will not be “because I am generally an extraverted person” (which would be the between-person effect) or because “I was already happy a few hours ago” (which reflect autoregressive effects) but either “because I am seeing my close friends and therefore I am happy” (contemporaneous effects) or “because I met

my goodfriends earlier and now I feel happy” (cross-lagged effects). Our results show that dynamic personality theories are best suited to explain and predict behavior, affect, and situational experiences. This has relevance also across a wide range of applied areas of psychology. In organizational psychology, for example, a lot of research has been conducted to understand how people react *in* situations (Tett & Burnett, 2003; Tett & Guterman, 2000; Ziegler & Horstmann, 2015; Ziegler et al., 2019). However, this does not inform us about how people will react *to* situations, at a later point in time; or how they will select, navigate, and perceive future situations based on previous behavior or affect. Future research interested in the temporal sequences must therefore employ modeling approaches that allow for answering such questions, such as, for example, continuous-time modeling.

Continuous Time

Time is continuous, that means, not all effects occur just from one measurement occasion to another. It is oftentimes unknown in what time span an effect will unfold. Our results showed that the effect of state happiness on extraverted behavior was negative, that is happier people were less extraverted later in time. This effect was estimated to peak at 6.20 hours. The effect that took longest to unfold was that of state happiness on state sociality, which was positive, but was estimated to peak after 11.16 hours. Although this time interval is quite long, it is the nature of affect to last (and thus potentially impact behavior) over at least several hours (e.g., Watson & Gray, 2007). Note furthermore, that two variables can have reciprocal effects on each other, but that these reciprocal effects may unfold at different intervals. This has several important implications.

First, and from a theoretical perspective, the time interval that is examined must be considered when making predictions about how one variable affects another. Quoidbach and colleagues (2019) showed that happiness and social behavior are negatively related across time—unhappy people seek out more social interactions (in our terms, higher state extraversion),

possibly to feel happy. That is, the authors also reported a negative effect across time². They argue that this can be explained by the hedonic-flexibility principle. It describes that the function “of affective states is to help individuals prioritize among short-term goals [...] and long-term goals [...]” (p. 2). Based on our results, a similar principle could drive the association between sociality and extraversion: Having satisfied one’s needs to social interaction (Denissen & Penke, 2008), one may choose to behave less extraverted later on. This is precisely the mechanism that dynamic personality theories propose (DeYoung, 2015; Revelle & Wilt, 2021; Wilt & Revelle, 2017), namely a feedback loop (or, more accurately, a feedforward control). Hence, the continuous time model used in the current approach allows modelling and detecting such feedforward controls in personality dynamics.

Second, and from an applied perspective, it is important to understand that the effects of one variable on another take time to unfold. Everyone knows that physical training leads to fatigue right after the exercise, but increased strengths at a later point in time (between 2–3 days). Similarly, in cognitive-behavioral therapy, patients are encouraged to engage in certain exercises that hopefully affect their well-being at a later point in time. Yet, this effect also takes time to unfold. Knowing how long this time interval can be could guide clinical counselling and practice, for example by designing a detailed schedule (similar to a physical exercise plan) based on empirical evidence.

Third, our result has ample methodological implications. When designing an experience sampling study for the assessment of inter- and intraindividual differences in daily life, a key

² Please note that a recent re-analysis of Quoidbach and colleagues’ data has shown that the effect is more likely positive (Elmer, 2021). Notwithstanding, the effect of one variable on another is contingent on the time-interval under investigation. In a reply to Elmer, Quoidbach et al. (2021) clarify that “when concurrent happiness is accounted for (potentially capturing unobserved changes between observations), the sign of the relationship flips”, then “results show that people seem particularly prone to seek social relationships when they have experienced a recent decrease in happiness” (p. 964). These results are (1) conceptually in line with our reasoning in this work, that is, controlling for other components/effects may lead to different estimates (even in sign) and (2) comparable to our results as we estimated a negative cross-lagged effect of happiness on extraversion.

concern is the sampling frequency (Eisele et al., 2020; Horstmann, 2020; Rintala, Wampers, Myin-Germeys, & Viechtbauer, 2019; van Berkel et al., 2019). When setting up the experience sampling schedule, it has to be decided when participants are invited to take the survey, how often they should respond to it, and over which period. More frequent assessments mean higher burden on the participant, but fewer assessments lead to less information. The previous literature that has examined this effect has compared different sampling schedules with respect to their downsides, such as drop outs (Eisele et al., 2020) or response compliance (Rintala et al., 2019). However, continuous time modelling provides relevant information for the sampling frequency based on the effect that is examined. Based on our results, the optimal sampling frequency for the examination of the relation of sociality, happiness, and extraversion might be between 6 and 12 hours, or 2–3 times per day (but see also discussions of optimal time intervals, for instance, in the work of Dormann & Griffin, 2015). Note that continuous-time model allows for unevenly spaced time intervals, both within participants and between participants, and estimation might also benefit from unequally spaced assessment (Voelkle & Oud, 2013).

Similarly, our results have implications for the analyses of intensive longitudinal data. Time series are often examined by regressing an occasion on the previous occasion (e.g., Quoidbach et al., 2019; Rauthmann et al., 2016), thereby completely ignoring the interval between assessment occasions. As our results show (see esp. *Figure 2*) and as we have argued in the introduction, the autoregressive and cross-lagged effects may change with a varying time interval. Furthermore, the different peak values (see Table 1) vary as well, some effects peak earlier than others. Ignoring this can have severe consequences for the effects examined: If the time intervals are too short or too long, one may miss the effect entirely. Alternatively, the time interval can be optimal for one cross-lagged effect, but not for the other; one would then erroneously conclude that one variable affects the other, but not vice versa.

Note that due to different data analytical procedures, it is not possible to compare the results presented in the current study to the results presented by Rauthmann and colleagues (2016). As mentioned earlier, Rauthmann et al. did not consider the length of the time interval in their analyses. Furthermore, they estimated each effect separately, instead of modeling all four effects in one model. It is therefore only possible to compare the effects with respect to their interpretation. With respect to the three variables sociality, extraversion, and happiness, all effects reported by Rauthmann et al. (2016) were positive. However, as our re-analysis shows, some of the effects presented here are negative, leading to a different interpretation. This highlights how the data analytical approach chosen may not only lead to different effect estimates, but also to different conclusions (Silberzahn et al., 2018).

In our presented model, within-person effects (contemporaneous and cross-lagged effects) are used to describe the phenomena within one person, although these effects were estimated from multiple persons. The effects are thus average within-person effects, that is, they describe one *prototypical* person. Yet, people may also differ in their moment-to-moment stability or within-person variability (Baird et al., 2006; Geukes, Nestler, Hutteman, Kűfner, & Back, 2017), but these inter-individual differences were not components in the current model. The effects for one single person might differ.

For individual diagnostics, it might be interesting to estimate those effects for one specific person. Fortunately, $N = 1$ estimation, as well as fully hierarchical models are also possible within the continuous-time modeling approach and the employed software ctsem (Driver & Voelkle, 2018). Of course, for $N = 1$ estimation between-person parameters need then be discarded from the model. It is also important to realize that for $N = 1$ estimation is that the required number of time points to obtain adequate parameter estimates is (very) large (Hecht & Zitzmann, 2021a). With the Sherman and colleagues' data at hand, we cannot engage in $N = 1$ estimations.

Limitations

In our study, we have exemplarily shown how (1) between-person effects, (2) contemporaneous effects, (3) autoregressive effects, and (4) cross-lagged effects conceptually and empirically differ. Some limitations must be considered. We have exemplified the differences between the three perspectives only for three variables. These three variables were chosen because they have been comparatively well examined in the previous literature (Kritzler et al., 2020; Quoidbach et al., 2019; Rauthmann et al., 2016) and were theoretically relevant (DeYoung, 2015). However, this does of course not reflect the whole range of human experiences. We have neither considered other domains (e.g., conscientiousness), nor have we integrated different domains in one model (e.g., the effect of state extraversion on state emotional stability), although it is possible that variables which are uncorrelated at the between-person level are meaningfully associated, interacting and influencing each other (Wilt & Revelle, 2017), at the within-person level (both contemporaneously as well as over time).

Although our primary goal was not to make a substantial contribution to the literature on sociality, happiness, and extraversion, our results provide an additional piece of information. When interpreting the substantial results of the current study, some limitations should nevertheless be kept in mind (see Sherman et al., 2015, for limitations, such as the lack of generalizability due to the undergraduate sample as well as the self-report measures used). As a limitation more specifically to the results presented here, the results may not generalize to a sample that has generally less control over their daily lives than presumably undergraduate students (e.g., young parents, working population). The generalizability of our findings is therefore limited, and future research could examine the relation between social situations or specific social interactions, the behavior in that situation, and affective states based on non-self-reported data (e.g., from mobile sensing) in other samples of persons and situations.

Conclusion

We have shown how dynamic personality theories can be modelled in a continuous-time framework. We have illustrated that between-person effects, contemporaneous effects, autoregressive effects, and cross-lagged effects are conceptually (and often also empirically) different from one another, but fit well into a dynamic understanding of personality.

Autoregressive and cross-lagged effects furthermore can differ depending on the time-interval under consideration. The examination of personality dynamics and the development of personality theories should take all of these components into consideration to provide precise theoretical accounts on how constructs of interest are related.

Using dynamic continuous-time models for modeling dynamic personality theories comes with various advantages. (1) Between-person effects, autoregressive effects, contemporaneous effects, and cross-lagged effects can statistically be disentangled, that is, they are “purified” from each other. This feature is not specific to continuous-time dynamic models, but also, for instance, present in discrete-time dynamic models. (2) Compared to discrete-time dynamic models, continuous-time models offer some additional advantages: (a) data from unequally spaced and individualized measurements (e.g., from Ecological Momentary Assessment (EMA)) can neatly be integrated, (b) dynamic effects can be explored for time intervals that were not in the design/data, and (c) comparisons of studies that used different time intervals are facilitated because discrete-time model parameters for any arbitrary time interval can be calculated. (3) Further, dynamic models allow for estimating measurement error variance for single-indicator constructs.

Supplementary Material

The supplementary material can be found here:

<https://figshare.com/s/a096775ad452d76421b5>

Data Availability

The data analyzed in this study is originally from Sherman et al. (2015) and was used with their permission. The data is available from Sherman and colleagues upon request.

Disclosure Statement

The authors report no potential competing interest.

Preregistration

This work is mainly a methods illustration and was therefore not preregistered.

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Table 1

Peak Standardized Cross-lagged Effects

Parameter	Δ_{peak}	Est.	SE	LL95	UL95
$a_{\text{peak,std,S} \rightarrow \text{A}}^*$	9.48	-0.39	0.06	-0.50	-0.27
$a_{\text{peak,std,S} \rightarrow \text{B}}^*$	9.24	-0.55	0.03	-0.62	-0.49
$a_{\text{peak,std,A} \rightarrow \text{S}}^*$	11.16	0.20	0.05	0.11	0.29
$a_{\text{peak,std,A} \rightarrow \text{B}}^*$	6.20	-0.48	0.06	-0.61	-0.36
$a_{\text{peak,std,B} \rightarrow \text{S}}^*$	9.92	-0.44	0.09	-0.62	-0.27
$a_{\text{peak,std,B} \rightarrow \text{A}}^*$	6.92	0.72	0.12	0.48	0.95

Note. LL95 and UL95 are the lower and upper limit of the 95% confidence interval. Δ_{peak} is the time interval length (in hours) for the peak standardized cross-lagged effect $a_{\text{std,peak}}^*$.

Between-person effects

Cross-lagged effects

Autoregressive effects

Contemporaneous effects

Figure 1. Conceptual schematic representation of the continuous-time model (center of plot) and model parameters (Panels A-D) for three variables: [1] S = Situation, [2] A = Affect, [3] B = Behavior. Panel A: Between-person effects: Individual traits $\mu_{j\infty}$ vary and covary. Panel B: Autoregressive effects and Panel C: Cross-lagged effects: Individual states θ_{jp} at time point p (light grey circles) are predicted by previous states $\theta_{j(p-1)}$ at time point $p-1$ (dark grey circles). Cross-lagged (and autoregressive effects) depend on the time difference Δ between time point p and $p-1$. Δ might vary over persons and pairs of consecutive time points (indicated by subscript $j(p-1)$). Panel D: Contemporaneous effects: Individual states θ_{jp} at time point p vary and covary. These (co)variances are assumed equal over time and persons.

Figure 2. Autoregressive and cross-lagged effects plots. S = Situation; A = Affect; B = Behavior. The shaded area represents the 95% CI.

Figure 3. Impulse response plots. In the upper plot, the progression of the system (i.e., all three variables) is displayed when variable Situation changes by 1 *SD* at the first time point and thus asserts effects on Affect and Behavior later on. The middle and lower plot show the progression of the system for an impulse in Affect and Behavior, respectively.