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Modeling dynamic personality theories in a continuous-time framework: An illustration

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Abstract

Objective: 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.

Method: In the current work, we illustrate how common components from these new dynamic personality theories may be implemented in a continuous time-modeling framework.

Results: As an empirical example, we reanalyze experience sampling data with $N = 180$ 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.

Conclusion: 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

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

1 | INTRODUCTION

Ever since the conclusion of the person-situation-debate, new theories of personality conceptualize personality as dynamic (Baumert et al., 2017; Danvers et al., 2020; DeYoung, 2015; Quirin et al., 2020; Revelle & Condon, 2015; Sosnowska et al., 2020). Dynamic personality theories incorporate two important insights from the person-situation-debate (Fleeson & Noftle, 2009): First, personality traits are stable entities that describe

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how a person thinks, acts, or feels in general (Funder, 2001; Roberts & DelVecchio, 2000; Roberts & Yoon, 2021). Stable personality traits are furthermore 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 et al., 2007; Soto, 2019). Second, dynamic personality theories incorporate variability as an aspect of personality. A person behaves differently in different situations (Baird et al., 2006; Fleeson, 2001; Mischel & Shoda, 1995) and even differently in similar situations (Horstmann et al., 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 (Wrzus & Roberts, 2017).

Dynamic personality theories, implicitly or explicitly, build a bridge between seemingly contrasting positions, namely the stability of traits, variability of states across situations, and malleability of personality traits in the long term. Despite the recent efforts of proposing dynamic personality theories (DeYoung, 2015; Fleeson & Jayawickreme, 2015; Jayawickreme et al., 2019; Mischel & Shoda, 1995; Quirin et al., 2020; Tett & Guterman, 2000; Tett et al., 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 et al., 2021b): situation perception, affect, and behavior. We further explore potential next steps that should be taken in the examination of dynamic personality theories.

1.1 | 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 et al., 2020; Sherman et al., 2015; Tett & Guterman, 2000; Tett et al., 2021). This evidence has led to a "synthetic resolution" (Fleeson & Noftle, 2009) of the person-situation debate (for an overview, see Jayawickreme et al., 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 all incorporate implicitly or explicitly such dynamic aspects of personality. Historically, these theories stem from the person-situation-debate and built on one another. As a solution to the debate, Mischel and colleagues suggested the Cognitive Affective Personality System (Dingess & Wilt, 2020; Mischel & Shoda, 1995; Shoda & Smith, 2004). The Whole Trait Theory (WTT; Fleeson, 2001; Fleeson & Jayawickreme, 2015) builds on and extends the CAPS model. More recently, Cybernetic Big Five Theory (CBFT; DeYoung, 2015) and the Cues-Tendency-Action model (CTA; Revelle & Condon, 2015) have even further extended these theories by incorporating the perspective of time, suggesting how different processes can influence each other. Yet, all theories have in common that they require modeling several variables simultaneously to describe 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 (Mischel, 1973; Shoda et al., 1993; Wright & Mischel, 1987). A person behaves consistently according to their idiosyncratic interpretation of the world around them (Mischel & Shoda, 1995). These characteristic patterns of behavior are described as *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 momentary behavior. Furthermore, *if…then*-contingencies can vary between persons; that is, the relation among the variables in the system is itself an interindividual difference.

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 et al., 2017). These distributions are stable over time (Fleeson & Gallagher, 2009; Jones et al., 2017). Their central tendency (e.g., the average) indicates the propensity of a person to manifest a certain behavior (but also affective states, momentary cognition or desires, Wilt & Revelle, 2015). 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 and its extension WTT are broader theories that suggest that persons and situations interact to produce momentary behavior. All theories discussed here (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. CTA, which relies on the Dynamics of Action theory (Atkinson & Birch, 1970), postulates that "traits can be seen as [interindividual differences in] rates of change in states in response to environmental cues" (Revelle & Condon, 2015, p. 70; Revelle & Wilt, 2021). 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. First, the CTA model directly incorporates learning processes: It means that the stimulation a situational 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), depending on a person's 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., We can only write this article *or* go out with our 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).

1.2 | Dynamic longitudinal modeling

A central element in dynamic personality theories is temporal relationship, that is, something earlier affects something later in time (e.g., as conceptualized as *if... then*-patterns in the CAPS theory mentioned above). In statistics, such effects are often called "cross-lagged" effects as there is a lag of time between the source and the outcome and one variable influences another variable. Prominent models that incorporate such cross-lagged effects are the vector autoregressive model (VAR; e.g., Lütkepohl, 2005) and the cross-lagged panel model (Selig & Little, 2012), which even has been labeled the workhorse of developmental psychology (Berry & Willoughby, 2017). Traditionally, these models treat time as discrete, meaning that the phenomena of interest exist only at specific points in time. As a consequence, there is a specific time interval length (or lag) between two consecutive points in time, and parameters that characterize dependencies of variables with respect to the interval length (such as the cross-lagged effects) depend on this specific time interval length. Thus, a cross-lagged effect describing the temporal interrelation of two variables varies in size depending on how long the lag between two points in time is. Therefore, cross-lagged effects from studies that use different time intervals are not directly comparable. Also, such discrete-time models rather require that all individuals in a study have the same spacing between measurement occasions (although there are approximate approaches for allowing for unequal spacing, e.g., by using "phantom variables", Voelkle & Oud, 2015, or by "resetting the time variable using scaling, shifting, and rounding", Asparouhov et al., 2018). Another approach for considering the dependency of cross-lagged (and other dynamic) parameters on the time interval length is continuous-time modeling. Here, time is treated as continuous and the observations at specific measurement occasions are “snapshots” of a continuously evolving phenomenon (for a comprehensible introduction of how discrete-time and continuous-time dynamic models are related, see the work of Voelkle et al., 2012). Thus, data from unequally spaced measurements can be naturally included. Also, once the continuous phenomenon is described by the estimated parameters of the continuous-time model, discrete-time parameters (e.g., cross-lagged parameters) for any arbitrary interval length can be calculated. This facilitates study comparisons as cross-lagged effects can be transformed so that they are based on the same interval length. Also, it is possible to calculate model-implied discrete-time cross-lagged effects for time interval lengths that were not in the data, thus continuous-time modeling allows for exploring the unfolding and dissipation of dynamic effects (Hecht & Zitzmann, 2021b). In summary, dynamic personality theories propose principles which correspond to cross-lagged effects from dynamic discrete-time and continuous-time modeling frameworks.

Several articles have employed dynamic models for the examination of dynamic personality theories, the most recent ones by Danvers et al. (2020) and Sosnowska et al. (2020). Sosnowska and colleagues used a Bayesian hierarchical Ornstein-Uhlenbeck model (BHOUM, Oravecz et al., 2016), while Danvers and colleagues tested a Change as Outcome model (COM, see also Butner et al., 2015). 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.

1.3 | Purpose and scope

The present article is a methods illustration. We illustrate how certain aspects of dynamic personality theories could be modeled in a continuous-time framework. We overcome the particular shortcoming of previous empirical works in personality psychology of not considering more than two variables together by integrating the modeling of the interplay of person and situation into one model. In light of some advantages of continuous-time over discrete-time modeling (i.e., easy integration of data from flexible longitudinal designs with unequal and individual spacing, facilitation of study comparisons, possibility to explore the time interval dependency of dynamic effects), we think that continuous-time modeling is a promising framework for modeling dynamic personality theories and will therefore use continuous-time modeling (instead of discrete-time modeling) for our illustration.

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). However, we do not explicitly test different dynamic theories against each other. Instead, we conclude with a discussion and future directions of implementing and developing dynamic personality theories, such that they may be tested against one another in the future.

2 | 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 for the three 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). It is important to note that the model presented here is just one possible implementation from the broad class of continuous-time models; for example, we refrain from modeling inter-individual differences in intra-individual effects across time, although the existence of such differences is of course suggested by personality theories. Instead, we focus on average dynamic effects estimated across all persons (e.g., comparable to fixed effects), and do not model individual, person-level dynamic effects (e.g., comparable to random effects).

2.1 | Between-person effects

Historically, personality psychology and psychological assessment were primarily concerned with the description,

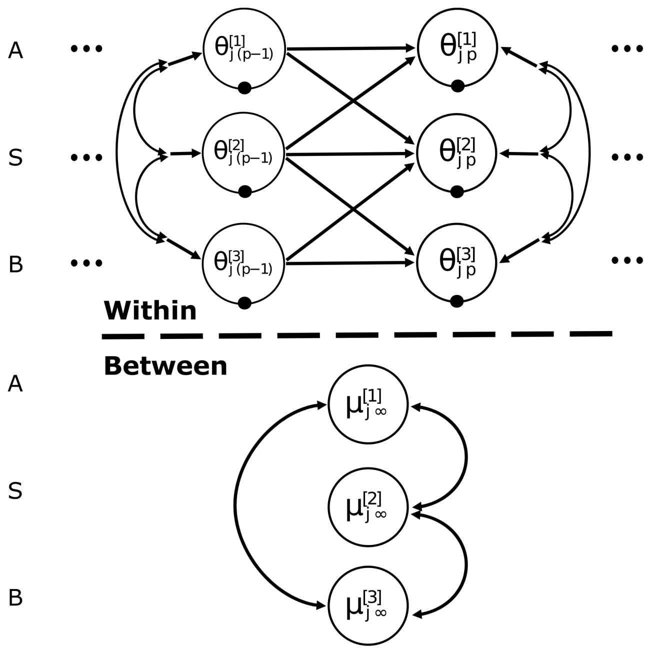

FIGURE 1 Conceptual schematic representation of the discrete-time structural part of the continuous-time model for three variables: [1] S = situation, [2] A = affect, [3] B = behavior. Upper part "Within": Individual states $\boldsymbol{\theta}_{jp}$ at time point *p* are predicted by previous states $\boldsymbol{\theta}_{j(p-1)}$ at time point *p-1*. 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)*). Individual residuals of states $\boldsymbol{\theta}_{jp}$ at each time point vary and covary. These (co) variances are assumed equal over time and persons and are the basis to derive contemporaneous effects. Lower part "Between": Individual traits $\boldsymbol{\mu}_{j\infty}$ vary and covary. First time point, the measurement part, and continuous-time constraints are omitted for clarity.

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, models for dynamic personality theories must contain 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 in the vector $\boldsymbol{\mu}_{j\infty}$ are assumed normally distributed with the average process means ($\boldsymbol{\mu}_{\infty}$) and a between-person process mean covariance matrix ($\boldsymbol{\Sigma}_{\infty}$). On the diagonal of this covariance 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 (lower part "Between") 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.

Besides process means, other parameters might be considered varying over persons as well, for instance, the contemporaneous, autoregressive, and cross-lagged effects discussed in the next subsections. However, in the present work, we limit ourselves to modeling between-person variance in process means and leave additional between-person effects for future research.

2.2 | 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 (upper part "Within") illustrates this component.

2.3 | 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 upper part "Within"). 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.

2.4 | 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 limitations. Someone who has functional limitations 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 negatively. Those how have higher extraversion have lower functional limitations later in time, and vice versa (Müller et al., 2018).

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 ($\mathbf{A}^{*}_{\Delta_{j(p-1)}}$). Figure 1 (upper part "Within") illustrates this component of dynamic personality theories.

3 | 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 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., 2021b; 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 et al., 2019; Rauthmann et al., 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 and 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.

3.1 | Data and procedure

The data set that we use in the current article has been analyzed in several previous articles before (Horstmann et al., 2021a, 2021b; 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 1 h apart. For each specific day of the study, all participants received their invitations at the exact same time.

3.2 | 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.

3.2.1 | 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 et al., 2017; Rauthmann, 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".

3.2.2 | 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.

3.2.3 | 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 endpoints "happy, positive—sad, negative". The scale was recoded such that higher values represent higher state happiness.

3.3 | 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.

3.4 | 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 7220. 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 $M_{\text{S}}=4.02$ ($SD_{\text{S}}=0.91$) for Situation, $M_{\text{A}}=5.21$ ($SD_{\text{A}}=1.01$) for Affect, and $M_{\text{B}}=4.51$ ($SD_{\text{B}}=0.96$) for Behavior. The average of descriptive within-person standard deviations is $M_{\text{SD,S}}=2.07$ ($SD_{\text{SD,S}}=0.49$) for Situation, $M_{\text{SD,A}}=1.39$ ($SD_{\text{SD,A}}=0.43$) for Affect, and $M_{\text{SD,B}}=1.65$ ($SD_{\text{SD,B}}=0.48$) for Behavior.

3.5 | 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.

3.6 | Analysis

We ran the continuous-time model using R 4.0.3 (R Core Team, 2020) and the R package ctsemOMX (Driver et al., 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 model[1] 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.

4 | 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.[2] 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 ($\sigma^2_{\text{fwS}}=2.50$ vs. $\sigma^2_{\text{wS}}=2.41$) and B ($\sigma^2_{\text{fwB}}=2.22$ vs. $\sigma^2_{\text{wB}}=1.96$), whereas a more pronounced difference prevails for variable A ($\sigma^2_{\text{fwA}}=3.11$ vs. $\sigma^2_{\text{wA}}=1.58$). In Table S2 (in the Supplemental Material), 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.

4.1 | Between-person effects

The between-person process mean covariances are also given in Table S1. For better interpretability, these covariances were transformed to correlations: $r_{\mu\text{AS}}=0.37$, $r_{\mu\text{BS}}=0.88$, and $r_{\mu\text{BA}}=0.50$. 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.

4.2 | Contemporaneous effects

The correlations based on the within-person covariances (Table S1) are: $r_{\text{wAS}}=0.18$, $r_{\text{wBS}}=0.49$, and $r_{\text{wBA}}=0.81$. 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.

4.3 | 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 decline and for $T \to \infty$ they will converge to 0 meaning that two states become independent. 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.

4.4 | 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

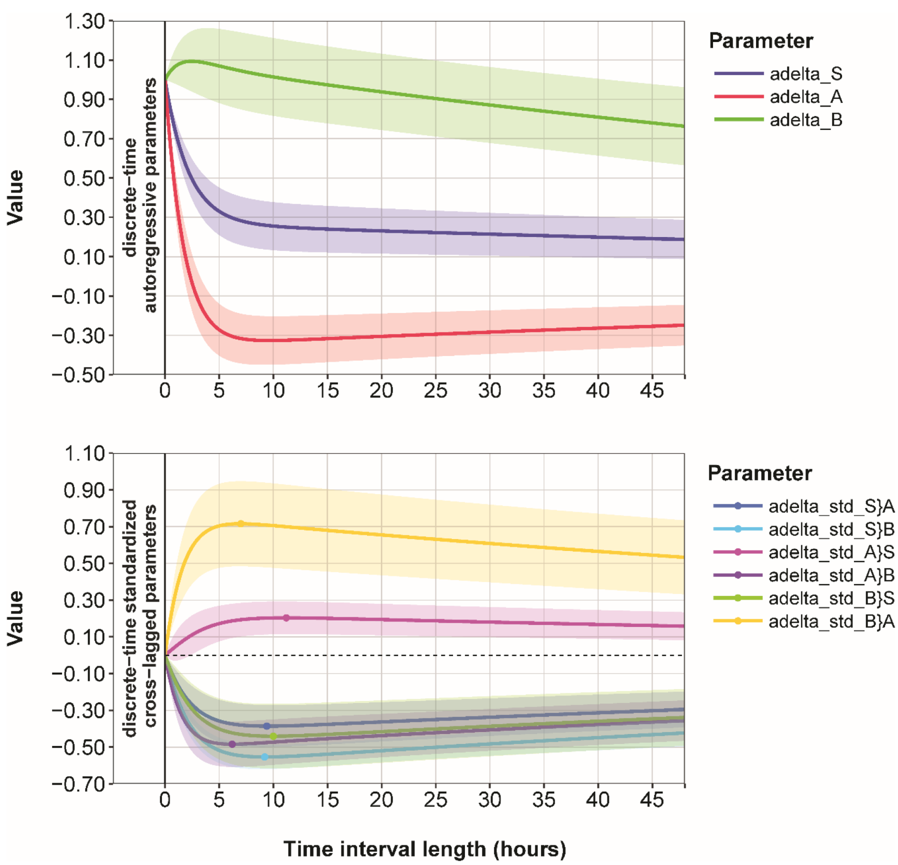

FIGURE 2 Autoregressive and cross-lagged effects plots. S = situation; A = affect; B = behavior. The shaded area represents the 95% CI.

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→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 $a^*_{\text{peak,std,S}\to\text{A}} = -0.39$ at the time interval $\Delta_{\text{peak,S}\to\text{A}} = 9.48$ 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 $1 \bullet SD_{\text{wS}} = 1.55$) is associated with a decrease of −0.39 *SD* in Affect (i.e., a decrease of $-0.39 \bullet 1.26 = -0.49$) 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 some have labeled as an *impulse*; see, for instance, Roskilly & Mikalsen, 2015; Lütkepohl, 2008). 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.

TABLE 1 Peak standardized cross-lagged effects

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

Note: *LL*95 and *UL*95 are the lower and upper limit of the 95% confidence interval. Δpeak is the time interval length (in hours) for the peak standardized cross-lagged effect $a^*_{\text{peak,std}}$.

5 | 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 modeled. 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 example of the 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.

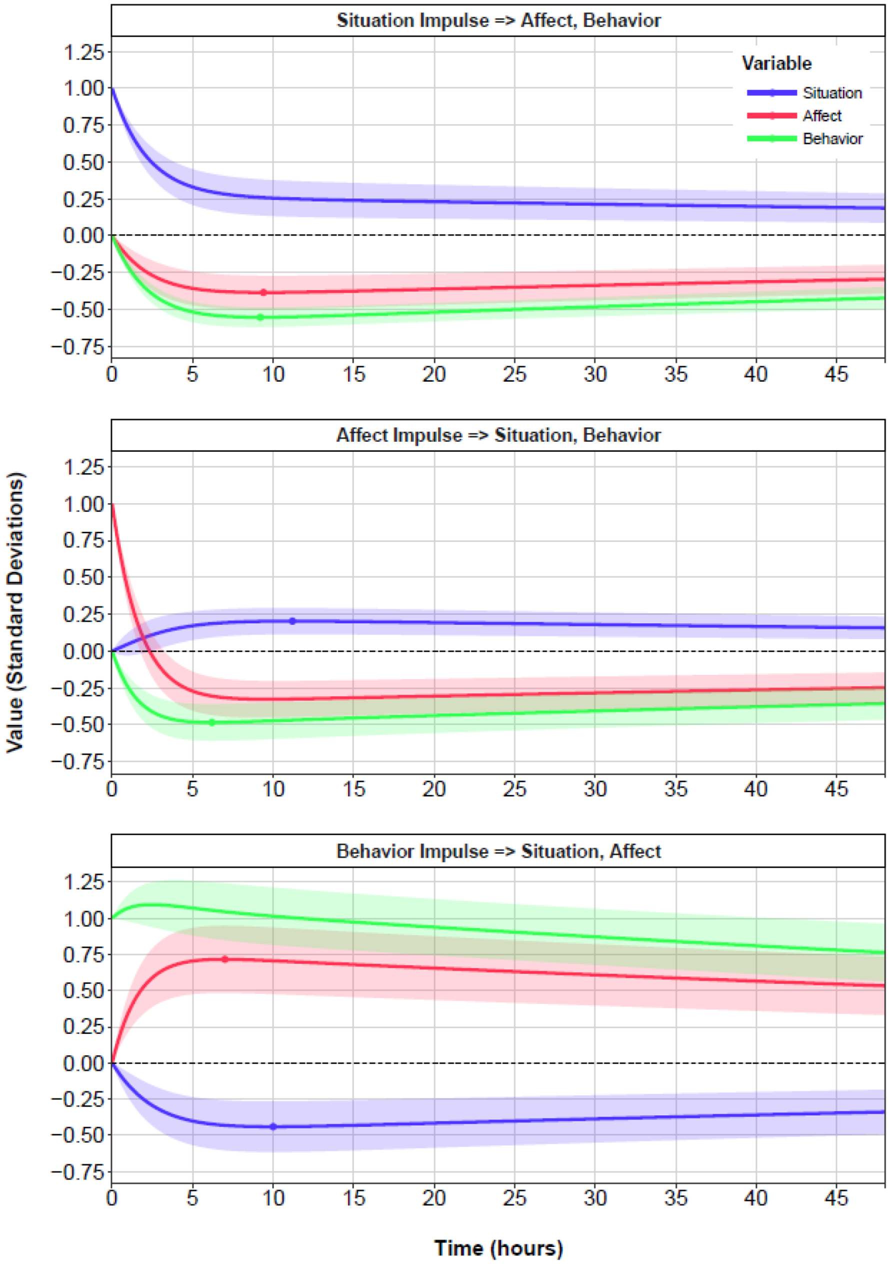

FIGURE 3 Impulse response plots. In the upper plot, the progression of the system (i.e., all three variables) is displayed when variable situation changes by 1 *SD* at the first time point and thus asserts effects on affect and behavior later on. The middle and lower plot show the progression of the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

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 over time, 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 et al., 2019).

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—persons 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 effect 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 good friends earlier and now I feel happy" (cross-lagged effects). Our results show that dynamic personality theories are best suited to describe and predict behavior, affect, and situational experiences—and, in the long run, potentially explain their interrelatedness. 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 et al., 2019; Ziegler & Horstmann, 2015). 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 there-fore employ modeling approaches that allow for answering such questions, such as, for example, continuous-time modeling.

5.1 | 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 et al. (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 time.[3] 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 modeling 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 and 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 counseling 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 intra-individual differences in daily life, a key concern is the sampling frequency (Eisele et al., 2020; Horstmann, 2020; Rintala et al., 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 modeling 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 directly compare the results presented in the current study to the results presented by Rauthmann et al. (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 et al., 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.

5.2 | Future of dynamic personality theories

Several different dynamic personality theories currently exist and make very similar statements about how personality unfolds in daily life. Yet, as is the case with many psychological theories (Eronen & Bringmann, 2021; Oberauer & Lewandowsky, 2019), it is currently not possible to directly compare these theories and test them against one another. The theories, as currently outlined, do not make precise enough claims that would allow falsifying one but keeping the other. One reason may be that the direction and the duration of the effects specified in these theories is not yet known. The current article may provide an initial step toward refining dynamic personality theories, such that they become more and more specific. In fact, with a dynamic modeling framework such as the continuous-time framework at hand, it may become easier and more straightforward for researchers to "analyze, specify, and formalize intuitions" about personality dynamics, and thus guiding us to an *open theory* of personality and to better science (Guest & Martin, 2021). One important ingredient for this endeavor is rigorous and replicable exploratory research on the manifestations of personality traits in daily life, a first step that we tried to take here.

5.3 | 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 it was not our primary goal 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.

6 | CONCLUSION

We have shown how dynamic personality theories can be modeled 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.

AUTHOR CONTRIBUTIONS

The authors declare the following contributions (as defined by http://credit.niso.org, accessed on 06 September 2022) to this article: MH and KTH: conceptualization, data curation, formal analysis, investigation, methodology, project administration, software, supervision, validation, visualization, writing—original draft, writing—review and editing; MA: conceptualization, methodology, validation, visualization, writing—review and editing; RAS: data curation, resources, writing—review and editing; MCV: conceptualization, methodology, supervision, validation, writing—review and editing.

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CONFLICT OF INTEREST

The authors report no potential competing interest.

DATA AVAILABILITY STATEMENT

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

ETHICS STATEMENT

The data analyzed in this study are originally from Sherman et al. (2015). Please see Ethics statements in the original work.

PREREGISTRATION

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

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ENDNOTES

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

[2] Univariate descriptive statistics describe one variable "on its own", that is, without considering other variables. Oftentimes, it may be interesting to derive descriptions of a variable that are "controlled" for (or "conditioned" on) other variables. In our model, the parameters (such as means and variances) are conditioned on (or controlled for) the other model parameters. Thus, univariate statistics might and often do differ from the corresponding conditional model parameters.

[3] 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.

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