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It's about time: Emphasizing temporal dynamics in dynamic personality regulation

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Abstract

People change over time. These changes are thought to represent some self-regulatory, dynamic processes. However, dynamic processes need to be distinguished from mere stochastic variation. Just as the Brownian motion of a dust mote does not help us understand the basic principles of classical physics, neither does random variation within an individual describe the complexity of self-regulatory processes. This regulation implies solving the problem of competing goals and desires within the constraints of situational presses. And what people feel, think, and do at one moment affects what they feel, think and do in the next moment. Thus, describing and explaining change over time must focus on dynamics in response to environmental cues and competing internal states. That is, we must include time and change over time in our models. We will outline the constructs needed to examine time explicitly in models of personality regulation, distinguishing between those that are not inherently temporal from those that are. We will discuss how computational modeling approaches may be used to study temporal dynamics and explain personality consistency and change. We will consider different time scales and discuss how an information processing perspective may inform choices regarding time scale and corresponding contexts for empirical studies.

KEYWORDS

latency, persistence, personality dynamics, personality regulation

1 | INTRODUCTION

Historically, research in personality psychology has pursued the fundamental goals of describing and explaining patterns of affect, behavior, cognition, and desire (the ABCDs of personality) across space and, critically, time (Revelle & Wilt, 2021). It is assumed that these patterns reflect regulatory processes that aim to solve problems related to competing goals within the constraints of the situational presses. Research on regulatory processes involves sampling moments in time, most commonly via experience-sampling methods (ESM: Conner et al., 2009). A single ESM report may be compared to a scene from a movie; an ESM report provides data about psychological experience (i.e., ABCDs) over a limited amount of time (e.g., a moment, a few minutes, an hour), similar to how a scene in a movie conveys a limited part of a complete story. Extending this analogy over time, multiple ESM reports represent slices of a person's uninterrupted psychological experience as multiple movie scenes are slices of an uninterrupted film reel. So imagine watching a set of scenes from a movie in random order and then attempting to understand the movie. If the chronology of the scenes could not be ascertained, one may attempt to analyze important characteristics (e.g., plot points, action sequences, romantic themes, etc.) in other ways. For instance, characteristics may be analyzed at the level of an individual scene or aggregated across scenes, or covariation of characteristics could be computed between scenes. Each of these strategies is similar to analyzing ESM data without accounting for time. Though some insights may be gleaned, it is likely that they would pale in comparison to the coherent understanding obtained through viewing the scenes chronologically. Analogous comparisons could be made for chapters in a book or movements in a symphony. These examples speak to the importance of considering time explicitly when attempting to understand dynamic personality regulation. We refer to this endeavor as the study of "temporal dynamics" (abbreviated henceforth as TD) to distinguish models that consider time explicitly from more general dynamic approaches in personality that do not necessarily model time (Kuper et al., 2021).

The study of TD is not particularly new in personality research, and indeed there are several current lines of research employing TD that are fruitful and influential (for a review, see Revelle & Wilt, 2021). However, we believe that TD are underutilized, particularly given the vast amount of research on personality processes that does not take time into account explicitly and instead focuses on within-person variation (see Beck & Jackson, 2021). Though we are not advocating that all personality research on repeated measures data model time, we think that neglecting to do so is a missed opportunity in many cases. Therefore, one major goal of the current manuscript is to reach an audience of personality researchers who are conducting research on personality regulation over time and who do not yet incorporate time into their models. For this audience, we provide an introductory overview of the different constructs and concepts that may be considered when developing TD models, distinguishing between constructs that are not inherently temporal and those that are. Furthermore, we describe the value of studying TD in contrast to focusing on within-person variation without considering time explicitly. As this special issue focuses on personality regulation, we detail why TD models are inherently regulatory. We then focus on how TD may be studied for individual time scales and integrated across multiple time scales. When discussing time scales, we propose that it may be useful to match different time scales to corresponding levels of information processing and situational characteristics. Throughout the manuscript, we emphasize personality constructs and individual differences variables, though we do mention approaches from other areas of psychology that focus less on individual differences (e.g., social psychology).

Though intended primarily for novice TD researchers, we also hope that this manuscript will be of use to those who are already experts in TD. Though to them most of the individual sections may be review, we believe that this manuscript presents the most comprehensive synthesis of our work and thinking on TD in personality, as it ties together different topics pertinent to TD that have been emphasized independently previous work, such as personality processes (Revelle, 1995), the ABCDs of personality (Wilt & Revelle, 2015), computational modeling (Revelle & Condon, 2015), environmental contexts (Wilt & Revelle, 2017), and levels of information processing (Ortony et al., 2005; Wilt, Oehlberg, et al., 2011). We also devote space to reviewing historical interest in TD models, as we do not believe that such a focused review has been done previously. We therefore hope that this paper serves as a useful reference and may help more advanced researchers consider key conceptual issues relevant to TD models.

2 | NON-TEMPORAL COMPONENTS OF A TEMPORAL DYNAMIC MODEL

To start off, we introduce parameters that do not inherently include time. That is, these parameters could be computed without knowing the chronological order of data points: ABCD personality states, environmental/situational characteristics, and stable individual differences. These parameters are important to include in TD models because they may (a) change over time as a function of temporal parameters and because they (b) may relate to or influence inherently temporal components. When we consider time explicitly in later sections, the inherently temporal parameters are linked in chronological order across multiple reports.

2.1 | ABCD personality states

A person's ABCD states, or short-term and relatively rapidly fluctuating personality characteristics (Fleeson, 2001), are of primary interest in TD models. Typically, researchers will be interested in understanding the time course of select ABCDs and how those ABCDs relate to each other across time; that is, the ABCDs may be considered individually and in relation to each other. The *level* of an individual state can be modeled as an *intensity* or *frequency*. For instance, an item could assess a person's level of state extraversion (intensity) or the number of times a person acted extraverted over a particular period of time (frequency). *Excitation* is when one state increases the occurrence of a different state, whereas *inhibition* is when one state decreases another state. Excitation and inhibition can be modeled as the within-person association of one state with another. The positive within-person association between state extraversion and state positive affect (Fleeson et al., 2002) is an example of excitation. Multiple ABCDs may be included in a model, each characterized by its own intensity, frequency, and probability of exciting or inhibiting other ABCDs (the total number of ABCDs in any one model will likely be small due to concerns about excessive complexity).

2.2 | Environmental and situational features are regulatory

"The environment consists of all psychologically relevant social, cultural, demographic, economic, family, relational, natural and physical features of common or impactful situations in a person's life." (Hopwood et al., 2022, p. 58). Given that the environment clearly regulates behavior, such as speed limits affecting driving and beds being used for sleeping, it seems natural to focus on environments in dynamics. However, the environment may be an overlooked source of regulation, as personality psychologists typically focus on internal regulatory processes (Carver & Scheier, 2009).

2.2.1 | Physical environments

The regulatory role of the physical environment has been emphasized historically and in other areas of psychology. William James wrote at length about habitual behaviors becoming ingrained by occurring repeatedly in the same environments (James, 1890). Individual examples of habitual regulation by the situation are readily at hand. B. F. Skinner famously had a writing room that he found conducive to productivity (Bjork, 1997). During the writing of this paper, one author (WR) observed that he would think about particular equations during the same portion of a daily walk.

Other people are also a prime source of regulation. Social psychological work shows that being a group of people can lead to deindividuation (Zimbardo, 1969), as seen in the events at the U.S. Capitol on January 6, 2021. People conform to the behavior of others in a group, even when the group is obviously incorrect (Asch, 1956). Introverts in the presence of Extraverts talk less than they do in the presence of Introverts (Antill, 1974; Revelle & Condon, 2015). The regulatory influence of other people and social norms is apparent in the following colorful example that demands to be quoted verbatim. "Imagine that you are walking down a city street and suddenly feel an urge to poop. If you don't poop on the sidewalk, then you are not being yourself. You are faking, and after that, it is a slippery slope—in everyday life it is impossible to say where faking ends and authenticity begins." (Hogan, 2005, p. 337). Additionally, in other species, the fact that small environmental changes of the group can lead to large shifts in behavior is evident in a murmuration of starlings or a school of fish. It would be unfortunate if TD models did not explore the environment to its full potential.

2.2.2 | Psychological situations

Recently, theoretical and empirical work on psychological situations relevant to personality has blossomed, providing a bevy of situational features to consider (Rauthmann & Sherman, 2020). For instance, one prominent model focuses on how much situations are characterized by duty, intellect, adversity, mating, positivity, negativity, deception, and sociality (DIAMONDS; Rauthmann et al., 2014). As with ABCDs, such features are characterized by their level (intensity or frequency). Excitatory and inhibitory effects of situational features on ABCD states should also be modeled. These relations between situations and personality states are referred to as situation contingencies (Fleeson, 2007a). There is a robust and growing literature linking situations to personality states (e.g., Rauthmann et al., 2016; Sherman et al., 2015), which may inform simulations of the strength of associations.

2.3 | Stable individual differences

ABCD states and environmental characteristics change relatively quickly over time as a person moves through life. In contrast, traits and other individual differences, such as motives (Atkinson & Raynor, 1974) and interests (Ackerman, 1997), cognitive abilities (Ackerman & Heggestad, 1997), and even physical variables (e.g., weight, Sullivan et al., 2007) are relatively stable, though they can change over time (e.g., Atherton et al., 2021). These variables are important to include in TD models first because they influence the probability of ABCD states or at least represent summaries of average ABCD state tendencies. This distinction is beyond the scope of this paper (but see Fleeson and Jayawickreme (2015) and Read et al. (2017) for discussions of whether stable individuals differences should be viewed as causes of states, outcomes, or both). Regardless of the direction of effect (i.e., from traits to states, or states to traits), people with higher levels of a given, stable trait will be more likely to be in the corresponding state. For instance, a person with high levels of agreeableness is more likely to exhibit polite and compassionate states (Fleeson & Gallagher, 2009). Therefore, as information about one's momentary states can be gained from knowing a person's stable trait level, including stable individual differences in TD models is highly recommended.

Individual differences may also interface with the environment through person- environment transactions, including selecting situations, evoking situational features, and reacting to situations (Fraley & Roberts, 2005). First, stable individual differences predict the probability of environmental characteristics through situation selection (Emmons & Diener, 1986). For example, more conscientious individuals are more likely to choose situations that call for dutiful behaviors (Wrzus et al., 2016). Second, people may draw out features of the environment proactively. For instance, a highly neurotic person may draw attention to the risky features of an environment and thereby increase the anxiety of others in the situation. Third, as people differ in their sensitivities to internal and external cues, individual differences may have implications for the connections (a) between ABCD states themselves and (b) between situations and ABCD states. For example, regarding connections between ABCDs, hunger states increased interest in food for normal weight individuals but decreased interest in food in overweight individuals (Nisbett & Kanouse, 1969). Steinberg and Yalch (1978) provided a conceptual replication of this finding. Staying within the psychological literature on eating, Herman and Mack (1975) showed complex relationships between multiple ABCDs; whereas restrained eaters (i.e., dieters) eat less than unrestrained eaters under control conditions, a preloading condition (consuming two milkshakes) caused restrained eaters to eat relatively more. These findings may be interpreted as a behavior (eating) leading to a cognitive appraisal of failure, undermining the desire limit food intake. See Mela et al. (1996) for a review of these and other findings relevant to eating ABCDs. Regarding connections between situations and ABCDs, appetitive situations produced more activated positive affect for more extraverted versus less extraverted individuals (Smillie et al., 2012).

2.4 | Stochastic models of within-person variation do not consider time explicitly

The parameters described above (ABCD states, environments/situations, and individual difference) are sufficient for models that simply predict within-person variation. Although within-person variation is inherently chronological, it is not necessary for statistical models of within-person variation to consider chronology explicitly. This becomes obvious in the example of a multilevel model (MLM) commonly used for studying within-person variation in personality (Fleeson, 2007b). Such models predict the probability of a certain ABCD state on a particular occasion from some combination of other ABCD states, situational characteristics, and individual differences.

The within-person effects from the MLM indicate the degree to which changes in a predictor associate with changes in the outcome *regardless* of time ordering. For instance, take an example where a researcher is interested in predicting within-person variation in state positive affect from another personality state (e.g., state extraversion), a situational characteristic (e.g., positivity), and an individual difference (e.g., trait extraversion). The researcher has collected data on state positive affect, state extraversion, and state positivity on 100 separate occasions for 100 participants, and the researcher also has one-time reports of trait extraversion from the participants. The typical MLM predicts positive affect *at any one moment* from state extraversion, state positivity, and trait extraversion *at the corresponding moment* (Bryk & Raudenbush, 1992); of course, states are different across moments, whereas trait extraversion remains stable. Thus, regardless of how the data are sorted or ordered prior to the model (e.g., chronologically, randomly), the result of the model will be the same. We did not need to know the order in which states occurred to find the typical within-person association. We will refer to these models as "stochastic," a term which refers more to probabilistic than mechanistic processes, because they focus on predicting the probability of within-person states. TD models are also probabilistic of course, yet by focusing on a precise understanding of how processes unfold they aspire to a more process-based understanding of phenomena.

Stochastic models are cornerstones of studying within-person variability. Personality psychologists have sought to understand the structure of within-person variations since the advent of P-technique factor analysis (Cattell, 1946). We refer the reader to excellent reviews of within-person variation in personality (e.g., Beck & Jackson, 2021; Jayawickreme et al., 2021; Kuper et al., 2021; Rauthmann, 2021), noting that these reviews also cover research on TD. As we transition to temporal components, our point is not to diminish the importance of stochastic models; to the contrary, we used them in much of our own work on dynamics (e.g., Wilt et al., 2017; Wilt, Funkhouser, et al., 2011). Instead, we want to emphasize that TD models afford unique opportunities.

3 | TEMPORAL COMPONENTS OF TEMPORAL DYNAMIC MODELS

As noted previously, stochastic models imply that ABCDs change independently of previous experiences and events. For instance, a positive within-person association between perceptions of adversity and state neuroticism means that increases in adversity correspond with increases in state neuroticism (Sherman et al., 2015). But what if many people take time to acclimate to adversity such that this positive association only holds for short intervals? Indeed, even lagged associations can differ markedly from concurrent associations (Beck & Jackson, 2020a, 2020b). These kinds of patterns could not be discovered without taking time into account. Temporal components allow for investigations into how ABCDs start, stop, and reemerge due to lawful properties.

3.1 | Brief historical context

Several classic works speak to the longstanding interest in TD. Although Kurt Lewin may be best known for a simple equation that epitomizes social psychology, he expounded more complex ideas about how fluid and shifting interactions of the environment and organism over time produce behavioral patterns (Lewin et al., 1935). Zeigarnik's (1927) discovery that interrupted tasks are better remembered than completed tasks revealed fundamental temporal aspects of learning and memory. Cattell (1957) gives perhaps the most thorough, early account of personality dynamics when discussing fluctuations and oscillations over time. Temporality is inherent in opponent process theories of motivation (Solomon, 1980; Solomon & Corbit, 1974), wherein the affect elicited by a primary stimulus is followed by the opposite affect, for example, the sequencing of pleasure and withdrawal after drug use. A single, classic study on the experiences of novice and experienced parachutists over the course of a jump stands out for its powerful use of graphical displays to convey the TD of anxiety (Fenz & Epstein, 1967). Novices tended to experience increasing anxiety that peaks at the jump, whereas experts' anxiety decreased from the time upon entering the plane until the jump, only to rebound shortly thereafter. Averaging anxiety over time would yield similar results for novices and experts, but their experience could not have been more different.

We delve further into some of the seminal work on goals given that goals are central to personality regulation (Austin & Vancouver, 1996). First, cybernetic models of self-regulation based on control theory explain *goal engagement and disengagement* over time (Carver, 1979; Carver & Scheier, 1982). That is, these models describe in detail the factors that contribute to pursuing certain goals over other goals as well as decisions to withdraw from goals: Such factors include the importance of the goals, overall progress toward the goals, and rate of progress toward goals. The distinction between approach goals (pursuing a positive outcome) and avoidance goals (avoiding a negative outcome) has been central to work on goal engagement and disengagement (Elliot & Thrash, 2002). Second, the construct of regulatory focus explains individual differences in *strategies that regulate goal pursuit* (Higgins, 1998). People with high levels of promotion focus will envision the rewarding aspects of achieving a goal and be motivated to realize these benefits, whereas people with high levels of prevention focus will attend to the punishing aspects of failure and work to avoid such negative consequences (Molden & Hui, 2011). Work on both goal engagement/disengagement and strategies that regulate goal pursuit complement each other without being redundant; indeed, note that the type of goal (approach vs. avoidance) and regulatory strategy (promotion vs. prevention) are theoretically independent. That is, a person may pursue an approach goal using either promotion or prevention focus, just as a person may attempt to achieve an avoidance goal using either regulatory strategy.

Computational modeling and statistical approaches are an integral part of the history of TD models in personality. Building on Jack Atkinson's groundbreaking work on the dynamics of action (Atkinson, 1957; Atkinson & Birch, 1970), Revelle (2008); Revelle and Condon (2015) developed a computational model for simulating the temporal course of environmental *cues*, motivational *tendencies*, and *actions*: the Cues-Tendencies-Actions (CTA) model. We will return to the CTA model later in the paper to illustrate some of the central parameters of TD models. The CTA model is just one example of a computational TD model of personality. For instance, Read et al. (2018) pioneered a neural network model that is capable of simulating behaviors over time based on motivations and situational affordances. TD models of affect (Kuppens et al., 2010) and personality states (Danvers et al., 2020; Sosnowska et al., 2019) incorporated concepts from mathematical models of dynamic systems such as equilibria, attractors, and repellers. Advances in statistical models of time series data (Hamaker et al., 2016) has already led to important discoveries about the TD of emotion, including insights into emotional patterns over time, such as lagged effects (Bringmann et al., 2018), inertia (Alessandri et al., 2021), and regularity (D'Mello & Gruber, 2021). Structural equation modeling (SEM) that incorporate time are still nascent but hold great promise for un covering the structure of emotional experience over time (Hamaker et al., 2021; Molenaar & Campbell, 2009). For a more complete review of historical and contemporary, see Revelle and Wilt (2021).

3.2 | Latency, persistence, and changing probabilities

TD models are fundamentally concerned with three temporal components: latency, persistence, and changing probabilities (Atkinson & Birch, 1970; Revelle & Condon, 2015). *Latency* refers to the time before experiencing or enacting ABCDs. For example, the desire to attend a party may build slowly for more introverted people compared to those who are more extraverted; an introverted person may require many prompts to attend a party whereas an extraverted person may accept the first invitation. Note the critical but nuanced distinction between latency and frequency. Frequency, which is the number of occurrences of an ABCD (e.g., partying), is the result of latency and (external and internal) prompting. *Persistence* is the time spent in ABCD states before stopping or exiting. More introverted people may attend a party, albeit with more prompting, but they may also leave earlier than their more extraverted counterparts. Here it is important to distinguish persistence (i.e., the duration of time) from intensity, which is the level of an ABCD across a particular duration.

Though we described latency and persistence individually, these concepts are intertwined (Atkinson & Birch, 1970). Persistence on one task is latency to start another. For example, a professor's longer persistence on absorbing tasks, such as writing and data analysis, creates greater latency to shift to more mundane administrative duties. Those duties are completed quickly, if at all possible (an example of low persistence), which decreases latency to resume writing and analyses. The inherent link between latency and persistence is perhaps more obvious when looking at relationships between behaviors necessary for survival and reproduction. In a classic demonstration of this principle, Halliday and Houston (1991) demonstrated that in oxygen rich environments, newts' persistence in underwater copulation increases in proportion to amount of oxygen in the atmosphere, which thus increases latency to breathe.

Changing probabilities refer to the shifts in a person's probabilities of ABCD states due to past and present experiences. These probabilities are tied to changes in latency and persistence; as latency decreases and persistence increases for any behavior, the probability of that behavior will decrease over time. For example, if an introvert enjoys several parties, that may lead to lower latency to attend and higher persistency at parties, thus increasing the probability of partying given an equal number of prompts. Increasing latency and decreasing persistence would lead to decreases in probabilities of a particular behavior.

3.2.1 | The CTA model

Taken together, latency, persistence, and changing probabilities explain the waxing and waning of ABCDs over time and, as illustrated above, may be examined independently from frequency and intensity. The TD models described in the previous section handle issues around latency, persistence, and changing probabilities differently. As the second author (WR) developed the CTA model (Revelle & Condon, 2015), we use it to give an example of how these principles may be simulated by computational modeling. In the context of TD in personality, computational models have the potential to fill explanatory gaps by directly manipulating computer-simulated aspects of individual differences, ABCD states, and the environment.

The CTA model is able to simulate the likelihood of a particular ABCD at a particular time and predicts changes over time in multiple ABCDs simultaneously. Cues from the environment stimulate tendencies, which are covert motivational states that in turn stimulate actions (functionally, any ABCD could be modeled as an "action" in this model). The strength of a given tendency (e.g., excitement about a potential social reward) is a function of environmental cues (e.g., smiling people), the strength of the connection between the cue and tendency (e.g., an individual difference variable such as extraversion), and the consummatory strength of a given action (e.g., conversing) upon the tendency. The probability to engage in a given action is a function of the connection between a given tendency and the action, and the inhibition of one action over another. Just two difference equations represent the formal mathematical notation of the relations between model parameters:

$$d\mathbf{t} = \mathbf{Sc} - \mathbf{Ca} \tag{1}$$

$$d\mathbf{a} = \mathbf{Et} - \mathbf{Ia} \tag{2}$$

where in an environment which affords cues for action ($\mathbf{c}$), cues enhance action tendencies. ($\mathbf{t}$) which in turn strengthen actions ($\mathbf{a}$). Across time, the model computes changes in tendencies ($d\mathbf{t}$) and changes in actions ($d\mathbf{a}$). Trait like individual differences parameters include $\mathbf{S}$, the sensitivity to cues, $\mathbf{C}$ the amount of satisfaction (consummation) achieved by doing an action, $\mathbf{E}$ the learned strengths of associations between tendencies and actions, and $\mathbf{I}$, the mutual interference between actions. (See Revelle & Condon, 2015, for more details.) This relation between variables is depicted graphically, making the concepts of latency, persistence, and changing probabilities readily apparent (Figure 1).

As it may not be apparent how the equations translate to simulated data, we next unpack the equations using a straightforward example that we later translate to the simulated data in Figure 1. In our example, we will focus on the tendency (**t**) for talking and action (**a**) of enacting talking behavior. For Equation (1), *d***t** could be modeled function of a person's trait extraversion (**S**) and environmental cues (**c**) such as number of people. In our example, for ease of interpretation, we will vary only S, trait extraversion. So, keeping c constant, the person's tendency to talk should increase as S increases. Yet we also see from Equation (1) that one's tendency to talk would decrease according to the amount of satisfaction one gets from talking (**C**) multiplied by the time spent actually talking (**a**). So in essence, Equation (1) shows that tendencies are affected by traits, cues from the environment, and the satisfaction derived from actions themselves. Equation (2) is focused on predicting change in talking behavior over time (*d***a**). This is a function of the t for talking at a given time multiplied by the strength of the connection between t and talking (**E**), or how directly tendencies are translated to actions. If multiple actions are modeled, we also see that *d***a** will decrease when competing actions are taking place as a function of the mutual interference parameter (**I**). Interference does not apply to the figure because we modeled one action only (talking), but it is easy to imagine that an anxious action would interfere with the talking. Looking at the figure, we can see that the concepts of latency, persistence, and changing probabilities readily apparent and vary as a function of trait extraversion (Figure 1). That is, the more extraverted one is, the longer persistence, lower latency, and increased probability of talking.

As a model of regulation, the CTA model can be applied to self-regulation (competing behaviors within individuals) or other-regulation (competing behaviors between individuals). Perhaps because it is more intuitively understandable in Figure 1 we show how talking behavior is regulated by the presence of others. When with more extraverted companions, the more introverted talk less. However, when in groups of fellow introverts, everyone talks about the same (see table 3 in Revelle & Condon, 2015).

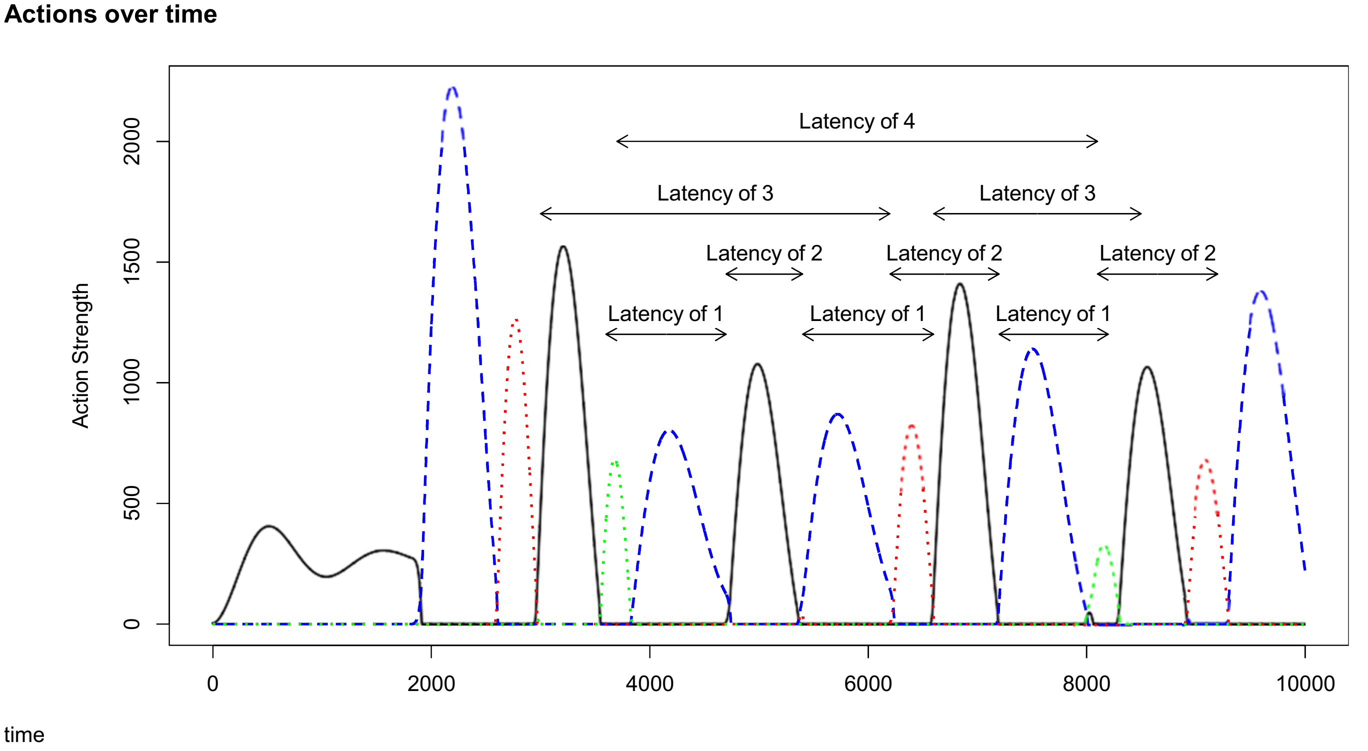

FIGURE 1 The sequencing of four behaviors reflecting differences in the strength of sensitivity to social cues (S from Equation 1; i.e., trait extraversion). The model can be applied to regulation within or between individuals. Thus, the talking behavior of four individuals differing in extraversion are shown. Each individual's behavior is regulated by the behavior of the others. Given normal levels of politeness, people do not interrupt each other and wait until the other person is finished. Line 1 (solid black represents the most extraverted, dotted blue the next most extraverted, etc. Total times spent talking are 43%, 40%, 11% and 6% for people with trait extraversion levels of t 4, 3, 2 and 1. Note how the most introverted participant (green dashed line) has the longest latency and least persistence in talking. Adapted from Revelle and Condon (2015) based on data reported by Antill (1974) and modeled with the `cta.15` function in the *psych* package (Revelle, 2021) in R (R Core Team, 2021).

It is apparent from Figure 1 that the CTA model (and indeed any computational TD model) may be used to model consistency and change over time, issues that are central to the study of personality development (Caspi et al., 2005). Figure 1 deals with a relatively short time scale (i.e., minutes), yet we have shown previously that extending the parameters over longer time scales, such as months and years, can reproduce patterns of personality development over corresponding time frames (Revelle & Condon, 2015). We therefore believe that there are major opportunities to integrate TD models into current theories of personality development (see McAdams et al., 2018). Though developmental theories do of course focus on change over time, we have not seen detailed considerations of temporal components such as latency, persistency, and changing probabilities incorporated in these theories.

There are of course some limitations to the current CTA model. It does not include a parameter specifying that actions can change the environment, which is desirable because people strive to actively create environments that are best suited for their survival and success (Bouchard, 2016). For instance, work on person-environment transactions shows that people can have proactive effects on situations (Rauthmann et al., 2016). Further, flexible learning components are needed (Sharp & Eldar, 2019). We are developing learning parameters that would simulate the development of action tendencies over time based on biological maturation and interaction with the environment. Another potential area worth looking into is adding higher level cognitive control parameters akin to executive functioning (Stuss, 1992). These parameters could possibly model situation selection and the ability to modify the strength of connections between (a) tendencies and actions and (b) cues and actions. Finally, the CTA model is theoretically agnostic (i.e., it has the ability to model any CTAs), yet it is sensible for TD models to be consistent with evolutionary and biological theories of individual differences (Del Giudice, 2021; Quirin et al., 2020). Some work has been done in this regard, as the model has been adapted to simulate the strength of biobehavioral systems in the Revised Reinforcement Sensitivity Theory (Brown, 2017; Brown & Revelle, 2021).

3.3 | Temporal dynamic models are inherently regulatory

The CTA model, like all TD models, inherently deals with regulatory processes. At the simplest level, regulation may be described by basic stimulus-organism-response (S-O-R) frameworks (Lewin, 1943). An organism responds to a stimulus to meet a certain need; it is likely that a hungry organism will consume food to satiate hunger, whereas an already satiated organism may forego the opportunity to eat to avoid becoming overfull. The CTA model is an obvious extension of S-O-R thinking; in the CTA model, the organism is conceptualized as the covert motivational tendencies that interact with environmental stimuli. As apparent in Figure 1, certain motivations rise to produce ABCDs and are consummated by the enactment of said ABCDs.

Though not depicted in the figure for the sake of simplicity, regulation involves more complex and evolving interactions between ABCDs. A person may behave in a certain way because of a particular desire, as illustrated by TD models of achievement motivation (Kuhl & Blankenship, 1979; Revelle & Michaels, 1976) and functional perspectives on Big Five traits (McCabe & Fleeson, 2012, 2016). Cognition controls behavior and perceives whether any adjustments are required to meet the desired affective states (Lawrence et al., 2002; Wilt et al., 2017). Behaviors also change environmental inputs (Powers, 1973), which are then perceived cognitively (and so on). As noted in the previous section, the CTA model does not yet simulate these effects of behavior on environments, however, that is a crucial part of regulation. Further, there are individual differences in these kinds of complex interactions, wherein people may differ in their regulatory processes and strategies. For instance, some people cognitively intervene relatively early when they are feeling negative emotions and are thus able to modify their feelings and behaviors adaptively, whereas other people intervene later and tend to suppress their behaviors and feel more negative emotions (Gross & John, 2003).

When applied to social interactions, the regulation is supplied by others. Given a basic modicum of politeness, that someone else is speaking inhibits one's speaking. This leads to a growth in the desire to speak among the listeners and a decay in the desire for the speaker. The slower the decay rate, the longer someone speaks. The greater the sensitivity the faster the growth of the desire to speak. Persistence in speaking reflects the regulatory balance between one's own desires, and the desires and behaviors of others. As we show in Figure 1, the latency before speaking is also an important measure of the temporal dynamics.

4 | CONSIDERING TIME SCALES, LEVELS OF INFORMATION PROCESSING, AND CORRESPONDING SITUATIONS

People are regulated by what happened in the past, what is happening in the present, and what they expect will happen in the future. The present in some sense is timeless, as it is always "now" (Bardon, 2013). The past and future can be so short such that they may be measured in milliseconds and as long as years, decades, or generations. One's own life reaches into the past back to birth and stretches into the future to death (with many believing that consciousness continues after bodily death). People are also influenced (a) by what happened before birth by historical events, as well as (b) by what they think will happen to the world and themselves after death. To see how we are regulated by the time beyond our own lives, we may look to the influences of past generations on our own (e.g., the effects of climate change) and to our own planning for the generations to come (e.g., preparing for climate change). Furthermore, as shown by the work on time perspective (Kairys & Liniauskaite, 2015; Raynor, 1969, 1970; Stolarski et al., 2015) there are individual differences in the time zones on which people tend to focus (e.g., past, present, or future) and the attitudes which they have about those times (e.g., positive or negative). Given that it is not realistic to cover all time scales in any study, we must choose the appropriate time span to measure, whether it be minutes and hours to months and years (Revelle, 1989). However, as we do not know much about how personality processes unfold across these time scales, we offer one potentially useful way to divide time that we hope may be fruitful. Specifically, we propose that it may be helpful to consider the level of information processing involved in the TD process in question, that is, whether the TD process is working at the reactive, routine, or reflective level (Ortony et al., 2005).

4.1 | Reactive, routine, and reflective processing

The *reactive* level is likened to stimulus–response information processing. It is rapid and efficient, occurring over the span of milliseconds to seconds. ABCDs are largely undifferentiated from each other. A person perceiving a snake in a field will simultaneously pause their behavior and feel anxious due to conflicts between approach and avoidance motivation (Wilt, Oehlberg, et al., 2011).

The *routine* level is largely automatic and controls everyday activities that unfold over minutes to hours. Low-level Cs about the future (i.e., expectancies) may be differentiated from ABDs. For example, as one folds laundry (B), there is likely some vague sense of satisfaction or dissatisfaction (A) that comes from moving rapidly or slowly toward the goal of finishing (D).

The *reflective* level encompasses higher cognitive functioning such as self-awareness and metaprocessing. Affects are elaborated and conscious plans guide nuanced behavior over months and years. The path to tenure for a university professor exemplifies reflective processing. Over several years, meticulous planning direct complex behavioral strategies pertaining to choices of topics to investigate and grants to pursue. Anxiety and excitement may be highly elaborated by cognitive content.

4.2 | Different contexts matter at different levels of information processing

At each level of information processing and corresponding time scale, environmental conditions (situations) are highly salient regulatory factors. When modeling the reactive level over milliseconds to seconds, the immediate situation is most important. Regardless of one's temperament or life history predisposes calm behavior, noticing a tornado on the horizon is likely to result in reactive anxiety.

When modeling behavior at the routine level over minutes to hours, immediate context is still relevant but may be expanded to encompass relevant tasks. For instance, teaching a course or playing a sport may result in predictable variations in ABCDs over one to several hours. People typically divide their day according to such routine tasks and rely on the clock to tell them when to transition to and from different tasks. Daily and weekly routines also carry regulatory implications. Indeed, mood is highly predictable based on the weekly calendar, as people predictably do different things on work days and off days (Larsen & Kasimatis, 1990).

Monthly and yearly calendars also regulate ABCDs, with reflection being the primary level of information processing involved. Professors plan out entire semesters. Yet, approaching deadlines may interfere with best-laid plans and result in a shifting allotment of time across more and less pressing concerns. The anticipated arrival of a new baby may inspire meticulous planning to answer pressing questions over up to nine months. What furniture should be bought? What are the safest car seats? Do we need a new car? What about a new house? Some expecting parents may come up with answers gradually, whereas others might wait until the baby is ready to be born. Reflective processing can even influence behavior over multiple years. The progression of graduate school epitomizes changes at the reflective level. Incoming students may think in terms of a stand-alone project that can be carried out over a year, but by the time they receive their Ph.D., they may be able to design programs of research that can span decades. This change is likely not the result of increased intelligence but careful reflection about one's interests and abilities.

4.3 | The micro and macro levels are intertwined

When deciding upon which level of information processing and time scale to study TD processes, no one level or time frame is "better" than any other. Rather, all are important and all relate to each other. Obviously, seconds turn into minutes, and minutes to hours, and so on. And just as climate is the long-term average of short-term fluctuations in weather states, personality traits are averages of personality states over time (Fleeson & Gallagher, 2009; Revelle & Condon, 2017). Using simulations, Revelle and Condon (2015) showed that TD processes on shorter time frames within the individual may aggregate to produce large between-person differences over much longer time frames. Theory and research on personality development increasingly reflects these ideas (e.g., Quintus et al., 2021). When shifting between or integrating across levels, it is important to realize that predictability will increase as one moves from examining few occurrences of ABCDs over shorter time frames to aggregating over longer time frames (Epstein, 1983).

5 | CONCLUSIONS

In the personality literature, the term "dynamic" has been used to connote the study of change and process (Kuper et al., 2021; Rauthmann, 2021). This is a perfectly fine way to use the term, however, it encompasses two broad classes types of models which have yet to be sufficiently distinguished: (a) stochastic models, which examine within-person variations without explicitly modeling time, and (b) TD models, which include temporal parameters and are focused on how within-person changes evolve chronologically. Herein, we have separated the components of dynamic models that are non-temporal (ABCD states, environments, individual differences) from those that are (latency, persistence, changing probabilities). We used the CTA model to show the connections between these components. The CTA model and all TD models are inherently regulatory, as a person's current and future ABCDs and environments depend upon their past ABCDs and environments. In contrast, stochastic models are not regulatory, as they depend only on the present. Furthermore, we offered some considerations for studying different timescales, namely matching the time scale with corresponding levels of information processing and situations. We hope that this serves to stimulate interest in TD models, as they offer uniquely powerful techniques for advancing the study of personality regulation.

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Joshua Wilt led manuscript writing, and William Revelle contributed to the writing and approved the manuscript.

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This article is theoretical and did not involve research subjects and therefore was exempt from ethics approval.

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