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From Intellectual Investment Trait Theory to Dynamic Intellectual Investment Trait and State Theory: Theory extension, methodological advancement, and empirical illustration

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ABSTRACT

This paper introduces Dynamic Intellectual Investment Trait and State Theory, an extension of Intellectual Investment Trait Theory. Our theory extension (a) centers on dynamic within-person effects of cognitive performance states on intellectual investment personality states and vice versa (i.e., reciprocal effects), (b) integrates within-person dynamics and developmental trajectories in cognitive abilities and intellectual investment traits, and (c) is embedded in a continuous-time modeling framework. Aligning personality theories with statistical models, we discuss the most appropriate model for testing Dynamic Intellectual Investment Trait and State Theory: a continuous-time model that combines dynamics and trends. We apply the Continuous-time Latent Curve Model with Structured Residuals (CT-LCM-SR) in an empirical illustration involving 204 German adults who were assessed roughly 100 times on cognitive abilities (working memory) and intellectual investment personality (interest).

1. Introduction

Reciprocal effects between psychological constructs are of central interest in many theories on personality and individual differences. For instance, Intellectual Investment Trait Theory posits that mutually reinforcing effects exist between intellectual investment traits (selected personality traits such as openness, intellectual curiosity, or interests) and cognitive abilities (Ackerman, 1996; von Stumm & Ackerman, 2013; Ziegler et al., 2012; Ziegler et al., 2018). Although clearly informative, Intellectual Investment Trait Theory is also restricted in some respects; for instance, it strongly focuses on longer term development and effects at the between-person level, whereas the interplay between within-person momentary expressions of investment personality traits and cognitive performance has been widely neglected so far.

In this paper, we therefore introduce an important extension of Intellectual Investment Trait Theory, which we refer to as Dynamic Intellectual Investment Trait and State Theory. Dynamic Intellectual Investment Trait and State Theory centers on dynamic within-person reciprocal effects between cognitive performance states and intellectual investment personality states that unfold over shorter periods of time (see also e.g., DeYoung, 2015; Revelle & Condon, 2015; Revelle & Wilt, 2021). In addition, Dynamic Intellectual Investment Trait and State Theory integrates within-person dynamics and average developmental trajectories in cognitive abilities and intellectual investment traits. The theory further strives for conceptual clarity regarding the understanding and recognition of "time" by making it explicit that cognitive abilities and intellectual investment traits manifest continuously within a person (even though they are observed only at selected time points). We introduce a model that is well-suited to test Dynamic Intellectual Investment Trait and State Theory: A Continuous-time Latent Curve Model with Structured Residuals (CT-LCM-SR) as recently proposed by Lohmann et al. (2023). The model combines growth and dynamic modeling, isolates trends from the dynamic components of the model (Lohmann et al., 2022; Lohmann et al., 2023) and

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is estimated in a continuous-time modeling framework. Continuous-time modeling is an important modeling technique that holds many advantages (e.g., the option to explore the unfolding and dissipation of dynamic effects, Hecht & Zitzmann, 2021a). Although increasingly popular in various disciplines, this modeling strategy is still relatively unfamiliar within the realm of personality psychology, which is still dominated by other modeling approaches (Zitzmann et al., in press), and only a handful of initial studies have explored its potential (e.g., Hecht et al., 2023). We present findings from an empirical illustration in which we employ a CT-LCM-SR to examine the reciprocal relationships between cognitive abilities (working memory) and interest, and in which we thus show how to align Dynamic Intellectual Investment Trait and State Theory with our statistical model. To this end, we use data from a sample of 204 German adults who were assessed roughly 100 times (across an individually varying period of 114 to 251 days) on working memory and interest. The data originate from the COGITO ("Cognition Ergodicity") study, which was conducted at the Max Planck Institute for Human Development in Berlin, Germany (Schmiedek et al., 2010a, Schmiedek et al., 2010b). Future directions for theory and method development are discussed and methodological recommendations are provided.

2. Intellectual investment trait theory

The interface of personality and cognitive abilities has sparked interest in psychological research for over a century (e.g., Webb, 1915). Intellectual Investment Trait Theory has provided a prominent perspective on associations between personality and cognitive abilities by proposing that personality traits, particularly so-called investment traits, are linked to cognitive abilities (Ackerman, 1996; Cattell, 1987; Chamorro-Premuzic & Furnham, 2004; von Stumm & Ackerman, 2013; Ziegler et al., 2012; Ziegler et al., 2018). Note that, although we refer to Intellectual Investment Trait Theory, we acknowledge that the name actually refers to a family of theories (Ziegler et al., 2012). The focus of the present work is on the temporal interplay between intellectual investment traits and cognitive abilities, as it is this temporal interplay that is part of all of these theories. The roots of intellectual investment trait theory date back to Cattell (1943, 1987), who posited that gains in crystallized intelligence over time accrue from the continued investment of one's largely innate fluid intelligence in a specific domain. Cattell (1987) also theorized that higher intelligence and the success that is related to it prompt increases in certain personality traits (see also Ziegler et al., 2012). Expanding on this idea, Ackerman (1996) highlighted in his intelligence-as-process, personality, interests, and intelligence-as-knowledge (PPIK) framework that selected personality traits, henceforth labeled intellectual investment traits, contribute to the development of cognitive abilities in terms of crystallized intelligence, above and beyond the contributions of fluid intelligence (see also, e.g., Chamorro-Premuzic & Furnham, 2004). Later, von Stumm and Ackerman (2013) advanced the theory by providing a systematization of intellectual investment traits and proposing that a variety of constructs span the intellectual investment trait construct space (e.g., need for cognition, typical intellectual engagement, interests, openness to experience). Further, a decisive addition to intellectual investment trait theory was made by Ziegler et al., (2012; see also Ziegler et al., 2015; Ziegler et al., 2018), who introduced the Openness-Fluid-Crystallized-Intelligence (OFCI) model to the field. Among other processes, the OFCI model hypothesizes a direct link between intellectual investment traits and fluid intelligence and pays attention to both openness, and, in later extensions, interests, as proxies for intellectual investment traits (Ziegler et al., 2018).

Intellectual Investment Trait Theory outlines two key hypotheses about the temporal interplay between cognitive abilities and intellectual investment traits. On the one hand, according to the environmental enrichment hypothesis, intellectual investment traits should lead people to experience more learning opportunities, prompting them to invest their time and effort in their intellect. This investment, in turn, is believed to contribute to cognitive growth over time (Raine et al., 2002; von Stumm & Ackerman, 2013; Trapp et al., 2019; Ziegler et al., 2012; Ziegler et al., 2018). On the other hand, the environmental success hypothesis captures the opposite influences of cognitive abilities on investment traits (e.g., Cattell, 1987; von Stumm & Ackerman, 2013; Ziegler et al., 2012). As such, cognitive abilities should precede investment traits, as higher levels of cognitive abilities enable individuals to better engage with and pursue a variety of learning experiences, subsequently feeding into the development of their intellectual investment traits (Silvia & Sanders, 2010; von Stumm & Ackerman, 2013). Importantly, the environmental enrichment and success hypotheses are not mutually exclusive, and instead, reciprocal relationships between intellectual investment traits and cognitive abilities are assumed (e.g., Bardach et al., 2023; von Stumm & Ackerman, 2013; Wettstein et al., 2017; Ziegler et al., 2012).

3. From intellectual investment trait theory to dynamic intellectual investment trait and state theory

Although Intellectual Investment Trait Theory has made important contributions, it does have certain limitations, such as its primary focus on between-person relationships and the neglection of states. To overcome some of these restrictions and foster fresh perspectives on the interplay between investment personality traits and cognitive abilities, the present paper introduces an extended version of the original theory to the field–Dynamic Intellectual Investment Trait and State Theory.

3.1. States are central to dynamic intellectual investment trait and state theory

Intellectual Investment Trait Theory has often been described as reflecting longer term developmental processes; hence, its environmental enrichment and success hypotheses and respective processes are presumed to unfold over longer periods of time (e.g., over several years), with studies typically employing yearly or biyearly assessments of cognitive abilities and intellectual investment traits (e.g., Bardach et al., 2023; Bergold et al., 2023; Bergold & Steinmayr, 2016; Wettstein, et al., 2017). In reformulating the initial theory into Dynamic Intellectual Investment Trait and State Theory, we argue that the shorter-term dynamic interplay between "momentary" intellectual investment traits and cognitive performance should be at the heart of the herein proposed theory extension. Momentary manifestations of personality traits in specific situations are referred to as personality states (Baumert et al., 2017; Horstmann & Ziegler, 2020). Although more commonly used in personality research than in research on cognitive abilities, the "state" concept is applicable to the cognitive domain as well (e.g., momentary manifestations of cognitive performance when children or adults participate in cognitive training; e.g., Ericson & Klingberg, 2023).

Personality states play an important role in dynamic personality theories, which conceptualize personality as a dynamic system (e.g., DeYoung, 2015; Revelle & Condon, 2015, for an overview, see Hecht et al., 2023). Not only do these theories offer a way to describe people in general terms (e.g., someone is an intellectually curious person), but they also explain how momentary behavior manifests in specific situations. Several propositions of dynamic personality theories are particularly relevant for the herein presented Dynamic Intellectual Investment Trait and State Theory. For instance, the Cues-Tendency-Action model (CTA; Revelle & Condon, 2015) specifies—among other things—that within a given situation, individuals show behaviors that are in line with their personality traits if they encounter cues that trigger such behaviors. In other words, a person perceives a situational cue, and depending on the person's tendency to react to this cue, a specific action is shown (Revelle & Condon, 2015, Revelle & Wilt, 2021; see also Hecht et al., 2023). Applying this reasoning to Dynamic Intellectual Investment Trait and State Theory, we propose that a situation involving a challenging cognitive task will serve as a natural activator of intellectual-investment-trait-related states. As such, when facing a challenging cognitive task, an individual can "react" to the task by increasing levels of state interest and immersing themselves deeply in it, an action that, in turn, will feed into the person's higher state-level performance. CTA further includes learning processes. For instance, when dealing with a challenging cognitive task, a person will be more likely to deeply engage with it depending on their previous experiences (e.g., last time it was enjoyable to engage in such a task).

Cybernetic Big Five Theory (CBFT; DeYoung, 2015), another dynamic personality theory, adopts principles of cybernetics, that is, the study of goal-directed, self-regulating systems (Austin and Vancouver, 1996; Carver and Scheier, 1998; DeYoung, 2010). Like CTA, CBFT recognizes that traits are contextualized in situations, meaning that they are conditional on the presence of specific classes of stimuli. In line with the operation of cybernetic systems, a cycle of five stages is proposed: (a) goal activation, (b) action selection, (c) action, (d) outcome interpretation, and (e) goal comparison. Outcome evaluations and feedback from the last stage feed directly into future actions. Further, processes of the five stages are often carried out in parallel rather than serially (DeYoung, 2015). The stages of CBFT can be transferred to Dynamic Intellectual Investment Trait and State Theory. Here, a goal is activated, for example, by a situational cue (e.g., a cognitively demanding task [situational cue] can prompt the goal to do well on this task). Next, behavior that is appropriate for achieving this goal is activated (e.g., working hard to solve the task, leading to high task performance). Individuals then interpret the outcome of the action ("Did I do well and why [not]?"), which provides feedback for future actions. Outcome interpretations can also be based on affect (e.g., "Did working on this task make me feel good about myself and my capabilities?"). This affective route aligns with reinforcement learning that focuses on how individuals seek to approach positive feelings and avoid negative feelings, which has been described as a strong learning mechanism for a variety of domains, including complex behaviors and personality (Caspi & Roberts, 2001; Wrzus & Roberts, 2017). Both cognitive and affective interpretation routes seem likely to impact later investment personality states (e.g., enjoying working on a cognitively challenging task contributes to becoming more interested or curious).

Several issues relating to the central hypotheses of Dynamic Intellectual Investment Trait and State Theory derive from the discussion of dynamic personality theories and the focus of Dynamic Intellectual Investment Trait and State Theory on dynamics between investment personality states and cognitive performance states. It becomes clear that we need to change our way of thinking about the environmental enrichment and success hypotheses if we focus on states in situations, which contrasts with initial Intellectual Investment Trait Theory's focus on longer term links between cognitive abilities and investment traits. Specifically, if we consider that we are now interested in state expressions of investment personality and cognitive performance at shorter intervals (e.g., assessed every day over a period of time), the assumption that a person would, for example, select themselves into a more intellectually stimulating environment following the assessment on Day 1, which has an effect on the assessment on the next day might not necessarily hold. Instead, situation-specific processes come into play and are needed to inform the respective hypotheses. Let us outline two examples to guide the restatement of the environmental enrichment and success hypotheses to match Dynamic Intellectual Investment Trait and State Theory. The examples capture two different pathways of influence, with each of them involving a cognitively challenging task, which, in accordance with CTA and CBFT, serves as a "cue" for activating specific behaviors.

Path 1 (cognitive performance state → investment personality state): You perform particularly well on a cognitively demanding task on a certain day (let us call this "Session X"). Hence, you can exploit your cognitive potential in this session, which positively affects outcomes (strong performance in the situation) and evaluations, including the feeling that the experience was rewarding. All of this likely makes you more interested or intellectually curious the next day when you also encounter a cognitively demanding task (in Session X + 1). In Dynamic Intellectual Investment Trait and State Theory, we call this the *situation exploitation* hypothesis, which proposes that higher levels of state cognitive functioning lead to subsequent higher levels of investment personality states.

Path 2 (*investment personality state → cognitive performance state)*: Imagine that you show high interest and enjoy working on a cognitively demanding task on a specific day (Session Y). This interest prompts you to explore several potential solutions, think more deeply about the questions, and work harder. You probably also try a new reasoning strategy (which might not immediately be more successful but may serve as a training bed for more advanced reasoning). Overall, the "investment" of your interest in this session likely helps you to perform better in Session Y + 1. In Dynamic Intellectual Investment Trait and State Theory, we call this the *situation exploration* hypothesis, which proposes that higher state investment personality expressions lead to subsequent higher levels of state cognitive performance. It should also be noted that Paths 1 and 2 can co-occur, meaning that situation exploitation and exploration processes can take place simultaneously. In addition, even though our examples centered on positive reinforcement processes, coupling dynamics can also be driven by negative reinforcement. For instance, if an individual perceives a task as too challenging and frustrating, which signals a lack of ability to them, they may show lower investment personality states the next time they deal with a similar cognitively challenging task. General dispositions (e.g., trait Openness to Experience, mastery-oriented motivational orientations, trait intelligence, self-concept of intelligence) could possibly explain why some people get frustrated and divest whereas others get frustrated but still invest.

To summarize, unlike the environmental enrichment and success hypotheses, the situation exploitation and exploration hypotheses build on closely coupled sequences of situations and strongly center on (shorter term) reinforcement and feedback loops. Nevertheless, we note that this state of affairs does not have to be incompatible with longer term development, which we will elaborate on in the Discussion when presenting future theoretical expansions of Dynamic Intellectual Investment Trait and State Theory. Further, not only does Dynamic Intellectual Investment Trait and State Theory reflect interindividual differences in people's level of interests and cognitive abilities, but it also acknowledges the existence of between-person differences in within-person dynamics (see also e.g., Di Blas et al., 2017; Fischer & Karl, 2023; Fleeson et al., 2007; Katana et al., 2020; McArdle et al., 2012; Neubauer et al., 2018; Wang et al., 2012). For instance, whereas for some individuals, cognitive functioning states may more strongly affect subsequent intellectual investment states, this effect may be less pronounced for other individuals.

Two important further issues warrant attention. First, we think that the principles of Dynamic Intellectual Investment Trait and State Theory should apply to different contexts (e.g., school, workplace, leisure-time cognitive engagement) and research settings, with some specificities. In terms of research settings, we differentiate between controlled laboratory research on the one end of the continuum and studies taking place in real-life dynamic contexts on the other end. Here, we argue that in real-life situations, in which individuals have more autonomy over their cognitive engagement, stronger effects may be observed. In addition, it may take longer to reach the "peak" effect of the reciprocal coupling of investment personality and cognitive functioning states as individuals can tailor and expand these processes to fit their daily lives and interests. Of course, there will be great variation between individuals, because, for example, some individuals do not or very rarely actively seek out situations involving cognitive activation or easily become frustrated. On the other hand, in a lab setting in which all individuals are exposed to the same cognitive task (e.g., as part of a training study), autonomy is minimal and the novelty of the task decreases. Relatedly, reciprocal effects between investment personality states and cognitive performance states should be smaller and the "peak" effect should be reached much earlier than in a naturalistic environment. Second, Dynamic Intellectual Investment Trait and State Theory can explain processes at different time scales. For example, recursive loops can unfold in a single situation (i.e., from moment to moment). To illustrate, working on a task that sparks one's state interest (e.g., a puzzle or an education videogame targeting complex numerical skills) impacts state performance, which then promotes state interest within this single situation. However, the processes of Dynamic Intellectual Investment Trait and State Theory are not restricted to single situations and can also be located on a time scale reflecting daily series of situations. Hence, we deem it possible that state cognitive performance on a cognitive task on one day (e.g., doing well on the videogame involving numerical skills) can give raise to higher state interest the next day (e.g., when playing the game again). By contrast, longer time scales, as reflected in assessments taking place every few months or every year, cannot grasp state-level interplays and are thus not suitable to test Dynamic Intellectual Investment Trait and State Theory.

3.2. *Dynamic intellectual investment trait and state theory reconciles a focus on within-person dynamics and developmental trends and respective between-person differences*

Intellectual Investment Trait Theory has primarily been framed in between-person terms, and relatedly, environmental enrichment and success processes have been studied as between-person phenomena. For example, Chamorro-Premuzic and Furnham (2004) elaborated on effects of intellectual investment traits on cognitive abilities and wrote: "It is now time to ask whether personality traits have any effect on the development of intellectual skills (and vice versa). This refers to the question of why some people are more able than others …" (p. 257; see also, e.g., Beauducel et al., 2007). More recently, however, Ziegler (2014) stated: "It is time to shift research attention towards factors influencing intellectual development which lie within persons …." (p. 2). We agree with Ziegler's statement, and the situation exploitation and exploration hypotheses that were described in the previous section are clearly framed in "within-person" terms. Dynamic Intellectual Investment Trait and State Theory therefore pays specific attention to dynamic within-person reciprocal effects between cognitive performance states and intellectual investment personality states.

Nonetheless, in addition to within-person dynamics, the theory extension accounts for between-person developmental trends. Hence, Dynamic Intellectual Investment Trait and State Theory posits that individuals differ in the trajectories of the growth of their cognitive abilities and intellectual investment traits (see also, e.g., Núñez-Regueiro et al., 2022). Importantly, Dynamic Intellectual Investment Trait and State Theory reconciles within-person dynamics and between-person trends, as states are best operationalized as deviations from a person's trait-like developmental trends in the theory. This operationalization is also highly relevant from a conceptual viewpoint. A justification for this stance is presented: Let us look at the following examples. Consider that person i becomes more curious (than person j) over time, and this curiosity leads to a greater increase in person i's cognitive abilities. This is an important insight, as it tells us about developmental trends in person i's traits in terms of curiosity and cognitive abilities and how the one is affected by the other. Consider another example: Person k might not be known to be the most curious person; however, on a certain occasion, person k is found to be more curious than what would be expected on the basis of the person's trait level of curiosity (e.g., because person k sees the value of a cognitive task for their everyday life or because person k simply enjoys cognitively demanding work on this specific day); hence, person k's state curiosity shows a positive deviation relative to their trait curiosity. If we incorporate insights into general developmental trends in person k's curiosity, we can even say that person k shows higher state curiosity than what would be expected on the basis of their (not terribly steep) developmental trend in curiosity. In turn, this deviation in state curiosity predicts a positive deviation from person k's state cognitive performance, meaning that person k can realize a stronger gain in cognitive performance than what would be expected on the basis of their respective average development in cognitive performance. The second example—if repeatedly experienced (i.e., repeated deviations from one's traits/developmental trends) and deemed successful—is critical for personality change (see Wrzus & Roberts, 2017) and likely plays a role in cognitive abilities too. Hence, Dynamic Intellectual Investment Trait and State Theory's operationalization of states as deviations from developmental trends is well-aligned with modern personality science.

Note that the refinement of the state component can easily be integrated into the situation exploitation and exploration hypotheses from the previous section. For example, for Path 1, we began describing the situation exploitation hypotheses with the following phrase: "You perform particularly well on a cognitively demanding task on a certain day …." This can be expanded to "You perform particularly well on a cognitively demanding task on a certain day—much better than suggested by the average of your development trajectory for cognitive performance …." Similarly, for Path 2, which focused on the situation exploration hypotheses, the statement "Imagine that you show high interest and enjoy working on a cognitively demanding task on a specific day …" can now be refined to "Imagine that you show high interest and enjoy working on a cognitively demanding task on a specific day. Your levels of interest on this certain day really stand out, as you are more interested than what would be expected on the basis of the average of your developmental trajectory for interest …." Certainly, there are individual differences in dynamics as well as in trends, and Dynamic Intellectual Investment Trait and State Theory therefore also includes between-person differences in dynamics and trends.

Lastly, as for the situation exploration and exploitation hypotheses, the context and research setting should be taken into account when thinking about trends. For example, in the context of a lab-based training study in which individuals work on the same cognitive tasks over an extended period of time, it seems likely that cognitive performance should show an initial increase (in line with the aim of a training study), that then eventually levels out (see also Jones et al., 2005). Investment personality states, by contrast, may decrease and then level out. Specifically, as individuals are exposed to the same repetitive task, their interest should first decrease before they get used to the nature of the task and their interest stabilizes. Accordingly, logarithmic trends seem to match this specific research setting best. In other contexts (e.g., naturalistic settings), different trend shapes are likely theoretically more plausible. Also, note that the situation exploration and exploitation hypothesis focus on *deviations* from these trends; hence, irrespective of the shape of the trend, it is hypothesized that positive deviations in cognitive performance states and investment personality states reciprocally influence each other.

3.3. *Dynamic intellectual investment trait and state theory makes it explicit that time is continuous*

Research and theory on intellectual investment traits has been mute about conceptions of time, a limitation that Dynamic Intellectual Investment Trait and State Theory seeks to overcome. Theoretically, processes that occur only at discrete time points can be distinguished from processes that exist continuously but are observed only at discrete time points (e.g., Hecht et al., 2019; Hecht & Voelkle, 2021; Hecht & Zitzmann, 2020, 2021a; Voelkle et al., 2018; Voelkle et al., 2012). Consequently, we should make the continuous nature of these constructs and their interplay part of our theories and choose methodological approaches that allow time to be treated as continuous (i.e., continuous-time models, e.g., Hecht et al., 2023; Voelkle et al., 2018). Methodologically, another benefit is that data from unequally spaced measurement points can naturally be integrated in continuous-time models. Moreover, based on the estimated parameters from continuous-time models, discrete-time parameters can be calculated for any time interval length (e.g., Hecht et al., 2019). As such, continuous-time modeling allows researchers to explore the unfolding and dissipation of dynamic effects (Hecht & Zitzmann, 2021a).

4. Defining the appropriate theoretical estimand to represent the situation exploitation and exploration hypotheses

As described by Lundberg et al. (2021), the theoretical estimand defines the target quantity outside of the statistical model and, thus, represents a precise statement of the research goal. To guide the empirical illustration reported below and provide a blueprint for future research on Dynamic Intellectual Investment Trait and State Theory, we outline theoretical estimands for the situation exploitation and exploration hypotheses. Intellectual investment personality states and cognitive performance states refer to deviations from mean trends in interest and cognitive performance, respectively.

What changes in levels of state cognitive performance would people be expected to realize after a certain time period if they were to increase their levels of investment personality states, accounting for their initial levels of and average developmental trajectories of cognitive abilities and investment personality traits (and vice versa)? Even more precisely, what is the average effect of intellectual investment personality states on later states of cognitive performance (and vice versa)?

The described theoretical estimands focus on dynamic within-person reciprocal effects between cognitive performance states and intellectual investment personality states as a key element of Dynamic Intellectual Investment Trait and State Theory, even though estimands could of course also be derived for other aspects of the theory.

The second building block of the theoretical estimand is the target population, defined as the set of units over which the unit-specific quantity is aggregated (Lundberg et al., 2021). We believe that Dynamic Intellectual Investment Trait and State Theory's hypotheses about the interplay between cognitive performance and personality are a central part of human architecture, and accordingly, the theory makes claims about situation exploration and exploitation processes in humans.

4.1. Linking the theoretical estimand to an empirical estimand and estimation strategy

As proposed by Lundberg et al. (2021), the transformation of theoretical estimands into empirical counterparts is a crucial initial step, followed by the selection of appropriate estimation strategies. Dynamic Intellectual Investment Trait and State Theory, as presented, primarily focuses on causal temporal effects. Therefore, adopting a longitudinal research design and a model from the extensive array of dynamic models seems to be the most suitable approach. In the forthcoming sections, we will address three key aspects: (1) Examining the challenges associated with maintaining causal consistency when transitioning from theory to empirical research. (2) Delving into the considerations surrounding research design and the selection of a specific model. (3) Providing a detailed description of the selected model and the associated empirical estimand.

4.2. Exploring the process of aligning the theoretical causal estimand with its empirical counterpart

Causal theories, such as the presented Dynamic Intellectual Investment Trait and State Theory, postulate one or more cause-effect relations. Thus, to investigate this type of theoretical estimand, a causal estimate should be used. Indeed, the majority of longitudinal models are typically employed for studying reciprocal effects. However, it is largely unnoticed that the often-used basic versions of these models do not exactly provide the estimates that researchers are looking for, because they do not provide proper causal estimates.

To obtain a causal estimator, it can be helpful to employ tools like Directed Acyclic Graphs (DAGs; Pearl, 2009) first. These tools may help to clarify the so-called identification assumptions for a causal effect, thereby linking the theoretical with the empirical estimand (Lundberg et al., 2021). For example, a DAG could clarify whether other personality states are confounders or not. The choice of a specific estimate often involves additional (statistical) assumptions, making it challenging to establish a one-to-one correspondence between the theoretical estimand and the estimate.

In our current study, we employ longitudinal modeling to approximate causal estimators. It should, however, be noted that whether these estimators can be considered causal estimators depends on whether one is willing to accept strong and most likely unrealistic additional assumptions (for an overview, see, e.g., Hübner et al., 2023). To give an example, although our model captures essential aspects of the theory, such as dynamics, it inherently assumes the absence of confounding variables—third variables that impact the results. Of course, if there are confounders, they *should* be measured and controlled for to ensure an unbiased estimate.

Considering that our assumptions seem overall unlikely and because appropriate causal estimates have not yet been developed for our specific modeling framework, we have made a deliberate choice to refrain from using causal terminology in both our model description and the reporting and interpreting of results.

4.3. Design considerations and selection of modeling approach and model

The above-defined theoretical estimand revolves around examining how variables influence each other from one time point to a subsequent one, spanning a specific time interval. These types of effects are commonly referred to as "cross-lagged effects." Given the current absence of well-established and strong causal insights in the domain of dynamic models, particularly concerning the mitigation of unobserved confounding (as mentioned earlier), we opt to use the term "cross-lagged coefficient" instead of "cross-lagged effects." This choice underscores our cautious approach, prioritizing the avoidance of causal claims when certainty is not absolute.

Furthermore, the theory suggests that during a specified time interval, the effect sizes reach their peak, implying that they are comparatively smaller during other time intervals. Therefore, to explore how cross-lagged coefficients vary based on different time interval lengths, it is essential to adopt a particular modeling approach coupled with a specific form of longitudinal design. The model must either explicitly incorporate the cross-lagged coefficients or utilize a parametrization that enables the calculation of these coefficients. One crucial design consideration is whether to choose a fixed interval length or variable interval lengths between measurement occasions, with the additional question in the latter case of determining the extent to which the interval lengths should vary. This decision should be made while considering the performance and interpolation capabilities of the chosen modeling approach and model. One appropriate modeling approach could entail applying multiple discrete-time cross-lagged models, such as the renowned RI-CLPM (Hamaker et al., 2015), to data from partial designs that encompass varying interval lengths. This approach would yield cross-lagged coefficient estimates for the chosen interval lengths. Linear interpolation could be used to derive the coefficient estimates for other interval lengths. An alternative modeling approach could encompass the selection of a model with the capability to integrate all data, regardless of whether it originates from fixed or varying time interval designs, while inherently offering inter- and extrapolation capabilities. Continuous-time models offer precisely this feature set (for a beginner-friendly introduction to continuous-time modeling, refer to Voelkle et al., 2012, and for in-depth insights into exploring dynamic associations with continuous-time models, see Hecht & Zitzmann, 2021a, 2021b). The fundamental approach in continuous-time modeling is to establish a connection between the system's direction and rate of change (velocity) with its specific position at a given time (for a detailed explanation, refer to the exceptional description in Ryan et al., 2018). Mathematically, this is accomplished by defining a first-order stochastic differential equation. The "integral form" (Ryan et al., 2018) or "solution" (Voelkle et al., 2012) of this equation includes the time-interval specific cross-lagged coefficient, which form the essence of our theoretical estimand. Hence, the continuous-time modeling approach does not directly conceptually align to our theoretical estimand, because our theory does not involve statements about velocities based on the system's location at a certain point in time. Instead, we employ continuous-time modeling as a sophisticated approach to flexibly estimate our theoretical estimands, which are the time interval-dependent cross-lagged coefficient. Regardless of how the measurement occasions are spaced in the design, continuous-time modeling can seamlessly interpolate and extrapolate, enabling the provision of cross-lagged coefficient estimates for any arbitrary time interval.

4.4. Setting up the model

In the following, we elucidate the process of estimating the empirical estimand within a particular model, namely, a variant of the Random Coefficients Continuous-Time Latent Curve Model with Structured Residuals (Lohmann et al., 2023). We systematically build the model in an instructional step-by-step manner.

In our Dynamic Intellectual Investment Trait and State Theory, we are concerned with the temporal interplay of intellectual investment personality and cognitive performance for a person; thus, there are values of two variables that we stack into a column vector $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} y_{cogn.performance} \\ y_{interest} \end{bmatrix}$. As we have multiple repeated measurements of these two variables, we add the subscript p, with $p = 1, \cdots, T$ being a running index denoting the time point (T is the number of time points), yielding $\mathbf{y}_p$. With these multiple measurements of the two variables, we introduce the predictions (cross-lagged coefficients) of one variable on the other and vice versa from one time point to the next (with the assumption of time-constant effects),

$$\mathbf{y}_p = \mathbf{A}^*_\Delta \mathbf{y}_{p-1} \tag{1}$$

where $\mathbf{A}^*_\Delta = \begin{bmatrix} a^*_{\Delta,y1} & a^*_{\Delta,y_2\rightarrow y_1} \\ a^*_{\Delta,y_1\rightarrow y_2} & a^*_{\Delta,y2} \end{bmatrix}$ is the autoregression matrix, which contains the autoregressive effects, $a^*_{\Delta,y1}$ and $a^*_{\Delta,y2}$, on the main diagonal and the cross-lagged coefficients, $a^*_{\Delta,y_1\rightarrow y_2}$ and $a^*_{\Delta,y_2\rightarrow y_1}$, on the off-diagonals. The Δ reflects the assumption of equal intervals between measurement occasions and that these parameters are bound on this particular time interval under study in discrete-time dynamic models. Because the predictions are usually not perfect, we add normally distributed error (often called process error):

$$\mathbf{y}_p = \mathbf{A}^*_\Delta \mathbf{y}_{p-1} + \omega_p \quad \text{with} \quad \omega_p \sim \mathcal{N}_2\left(0, \mathbf{Q}^*_\Delta\right) \tag{2}$$

where $\mathbf{Q}^*_\Delta = \begin{bmatrix} q^*_{\Delta,y1} & \\ q^*_{\Delta,y_1y_2} & q^*_{\Delta,y2} \end{bmatrix}$ is the lower triangular process error covariance matrix.

So far, we have defined the targeted cross-lagged coefficients in discrete time for one person. Due to the discrete-time assumption, they depend on the specific time interval between the measurement occasions. However, as mentioned earlier, our Dynamic Intellectual Investment Trait and State Theory necessitates the estimation of dynamic parameters for multiple time intervals. Therefore, we are now shifting our approach to modeling the velocity $d\mathbf{y}(t)$ at time t using a stochastic differential equation:

$$d\mathbf{y}(t) = (\mathbf{A}\mathbf{y}(t))dt + \mathbf{G}d\mathbf{W}(t) \tag{3}$$

where $\mathbf{A}$ is the drift matrix, $\mathbf{G}$ is the Cholesky decomposition of the diffusion matrix, and $d\mathbf{W}(t)$ is randomness from a Wiener process. The interested reader is referred to papers by Hecht et al. (2019), Hecht and Voelkle (2021), Hecht and Zitzmann (2021a,b), Lohmann et al. (2022, 2023), Oud and Delsing (2010), Voelkle et al. (2012), Ryan et al. (2018) for details on the intricacies of continuous-time modeling. See also Table 1 in the article by Hecht and Voelkle (2021) for an overview of discrete-time versus continuous-time terminology. Most important for the current work is that the continuous-time drift matrix $\mathbf{A}$ (with auto-effects on the main diagonal and cross-effects, $a_{y_1\rightarrow y_2}$ and $a_{y_2\rightarrow y_1}$, on the off-diagonals) is the equivalent to the discrete-time autoregression matrix $\mathbf{A}^*_\Delta$ (with interval-specific autoregressive effects on the main diagonal and interval-specific cross-lagged coefficients, $a^*_{\Delta,y_1\rightarrow y_2}$ and $a^*_{\Delta,y_2\rightarrow y_1}$ on the off-diagonals) and that discrete-time autoregression matrices for any time interval Δ can be calculated from the continuous-time drift matrix $\mathbf{A}$ (see, e.g., the equations in the Appendix of papers by Hecht & Voelkle, 2021, and Oud et al., 2010). Besides a conceptual alignment of theoretical conceptualizations of time, the continuous-time modeling technique equips us with advantages, such as an inherent handling of individually varying designs and the possibility to explore the unfolding and dissipation of cross-lagged coefficients (Hecht & Zitzmann, 2021a). In fact, one interesting way of reporting results from continuous-time analysis is discrete-time plots of cross-lagged and autoregressive coefficients (see our Fig. 2 in the empirical illustration section) in which the estimates (y-axis) of the dynamic parameters are depicted depending on the time interval length (x-axis) (see Fig. 3).

So far, we have defined the targeted cross-(lagged)-effects within a continuous-time conceptualization. Besides dynamic effects, our Dynamic Intellectual Investment Trait and State Theory includes long-term trends, that is, a changing trait level around which states vary. To disentangle our empirical estimands of cross-(lagged)-effects from trends, we use modeling strategies from Lohmann et al., (2022, 2023). In a nutshell, these authors incorporated trend modeling into continuous-time modeling by using the "measurement component" (see the original works for details), thereby creating a "best of two worlds" combination of dynamic modeling and growth curve modeling, which makes it possible to include polynomial and exponential terms to model linear, nonlinear, and exponential trends.

Based on our theory extension, we consider logarithmic trends as the most plausible for both variables, and these trends can also be integrated via the measurement component. Following, for instance, Bryk & Raudenbush (2002), logarithmic growth curves can be modeled using the equation:

$$\mathbf{y}_p = \mathbf{b}_0 + \mathbf{b}_1 log\left(t_p\right) + \varepsilon \tag{4}$$

where $\mathbf{b}_0$ are the intercepts, $\mathbf{b}_1$ are the growth rates, $log\left(t_p\right)$ is the natural logarithm of time,[2] and ε are the (homoscedastic) error terms. In the CT-LCM-SR, the dynamic part is separated from the trend component with the measurement equation and forms the eponymous "residual" process (Lohmann et al., 2022; and see, Curran et al., 2014; Hamaker, 2005 for the discrete-time counterparts). Therefore, we can rewrite the dynamic DT formula from above as a process of residuals from the logarithmic trend:

$$\mathbf{y}_p - \left(\mathbf{b}_0 + \mathbf{b}_1 log\left(t_p\right)\right) = \mathbf{A}^*_\Delta\left(\mathbf{y}_{p-1} - \left(\mathbf{b}_0 + \mathbf{b}_1 log\left(t_{p-1}\right)\right)\right) + \omega_p \tag{5}$$

Combining both equations and using the well-known equation relating continuous-time auto effects and discrete-time autoregressive effects ($\mathbf{A}^*_\Delta = e^{\mathbf{A}\Delta t}$, e.g., Oud et al., 2010; Voelkle et al., 2012) we can write:

$$E\left[\mathbf{y}_p\right] = \mathbf{b}_0 + \mathbf{b}_1 log\left(t_p\right) + e^{\mathbf{A}\left(t_p - t_{p-1}\right)}\left(E[\mathbf{y}_{p-1}] - \left(\mathbf{b}_0 + \mathbf{b}_1 log\left(t_{p-1}\right)\right)\right) \tag{6}$$

[2] Note that the logarithm is not defined for negative values and zero. This has to be considered when choosing the scale of the time variable. For example, we can encode the first measurement occasion as $t_1 = 1$.

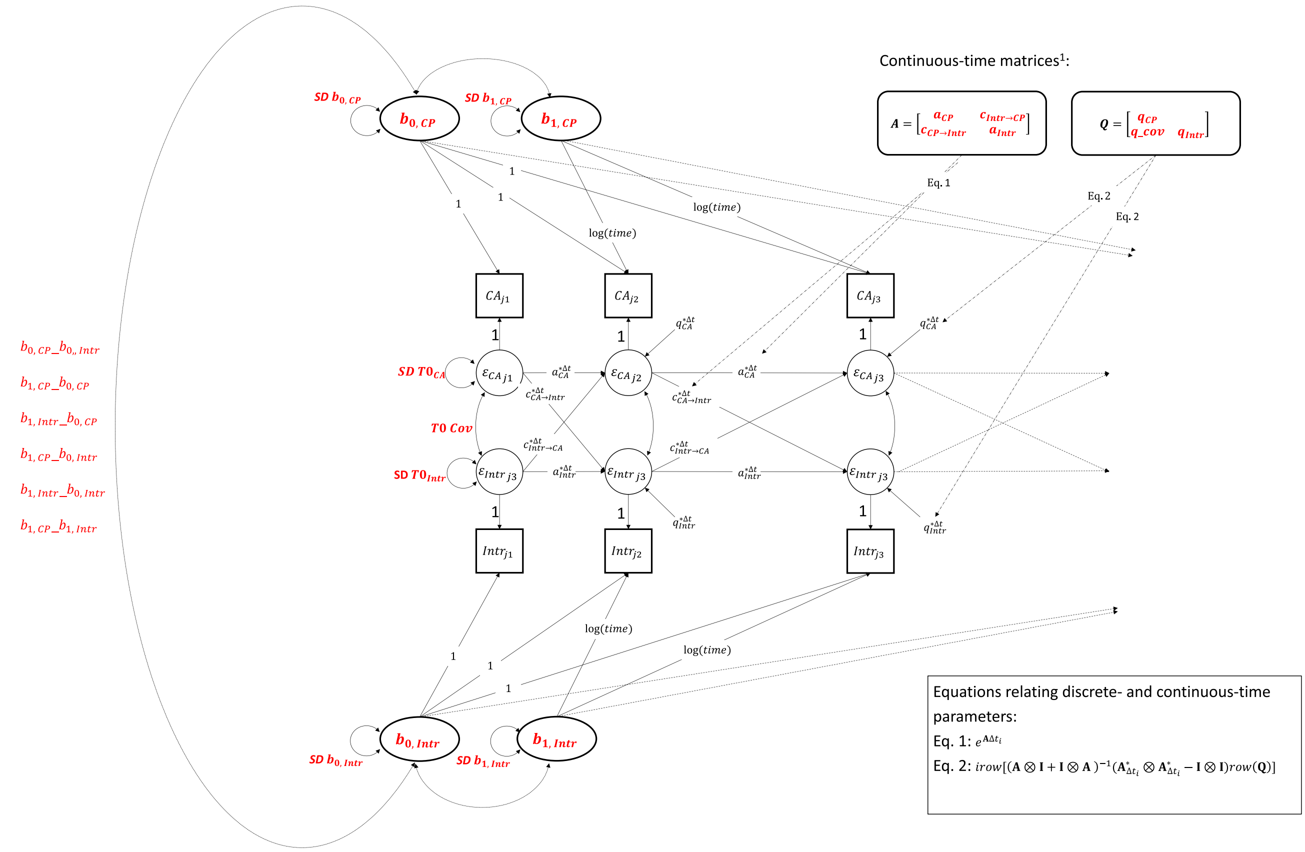

Fig. 1. Path diagram of the CT-LCM-SR with logarithmic trend component, with all estimated parameters represented in red letters. [1] Several arrows from the continuous-time matrices to the dynamic parameters in the diagram have been removed for clarity. However, all autoregressive (a^*) and cross-lagged (c^*) coefficients of the path diagram should be connected to the drift matrix **A**, and all process errors (q^*) should be connected to the diffusion matrix **Q**. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 1 shows a path diagram of the complete model, combining logarithmic trend component and continuous-time dynamics (details how to technically implement this model in R can be found in the Supplemental Material on the Open Science Framework, OSF; https://osf.io/c5sna/).

Now, our empirical estimand of cross-(lagged)-effects is controlled for trends but still defined for just one person ($N = 1$ scenario). As we want to make assertions about how people function in general (i.e., the average person) and not only about a specific person, we develop our single-person estimand further into the average across individual cross-(lagged)-effects ($N > 1$ scenario). Thus, our population changes from one specific person to the population of all persons. To this end, technically, we need a subscript j with $j = 1, \cdots, N$ (with N being the number of persons) on all mathematical symbols that denote individual values or parameters. For instance, substituting these person-specific parameters into Equation (6), the equation becomes:

$$E[\mathbf{y}_{jp}] = \mathbf{b}_{0j} + \mathbf{b}_{1j} log(t_p) + e^{\mathbf{A}_j(t_p - t_{p-1})}\left(E[\mathbf{y}_{j(p-1)}] - \left(\mathbf{b}_{0j} + \mathbf{b}_{1j} log(t_{p-1})\right)\right). \tag{7}$$

At this point, we may also introduce individually varying time points (implying individually varying time intervals) by adding subscript j also to the time points (see, for instance, Table 1 in the work of Hecht et al., 2019, for an illustrative example of such "unequal-interval individualized designs"):

$$E[\mathbf{y}_{jp}] = \mathbf{b}_{0j} + \mathbf{b}_{1j} log(t_{jp}) + e^{\mathbf{A}_j(t_{jp} - t_{j(p-1)})}\left(E[\mathbf{y}_{j(p-1)}] - \left(\mathbf{b}_{0j} + \mathbf{b}_{1j} log(t_{j(p-1)})\right)\right) \tag{8}$$

Furthermore, we may introduce distributional assumptions for the parameters. Specifically, we assume a multivariate normal distribution for the auto-effects, cross-effects ($a_{j,y_1 \to y_2}$ and $a_{j,y_2 \to y_1}$), diffusion (co) variances, and all intercept and growth components. The mean vector of the normal distribution contains the average value of each parameter, and the covariance matrix contains the between-person (co)variances of these parameters. Particularly, the mean vector contains the means (over persons) of the cross-coefficients, $a_{y_1 \to y_2}$ and $a_{y_2 \to y_1}$, which can be used to calculate mean interval-specific cross-lagged coefficients, $a^*_{\Delta, y_1 \to y_2}$ and $a^*_{\Delta, y_2 \to y_1}$, representing our final empirical estimands that match the theoretical estimands.

The estimands and the other model parameters can be estimated, for instance, in a structural equation modeling framework using a maximum likelihood (ML) approach, where the model parameters are estimated in such a way that the likelihood of the data given the model parameters is maximal. Usually, numerical optimizers are used for this task. Alternatively, a Bayesian framework could be used, where posterior distributions of parameter are the central targets. Often, the posterior distributions are simulated using Markov chain Monte Carlo (MCMC) methods. Examples of suitable software for estimating our model are OpenMx (Boker et al., 2017) and Stan (Carpenter et al., 2017). The R packages ctsemOMX and ctsem (Driver & Voelkle, 2018; 2021)

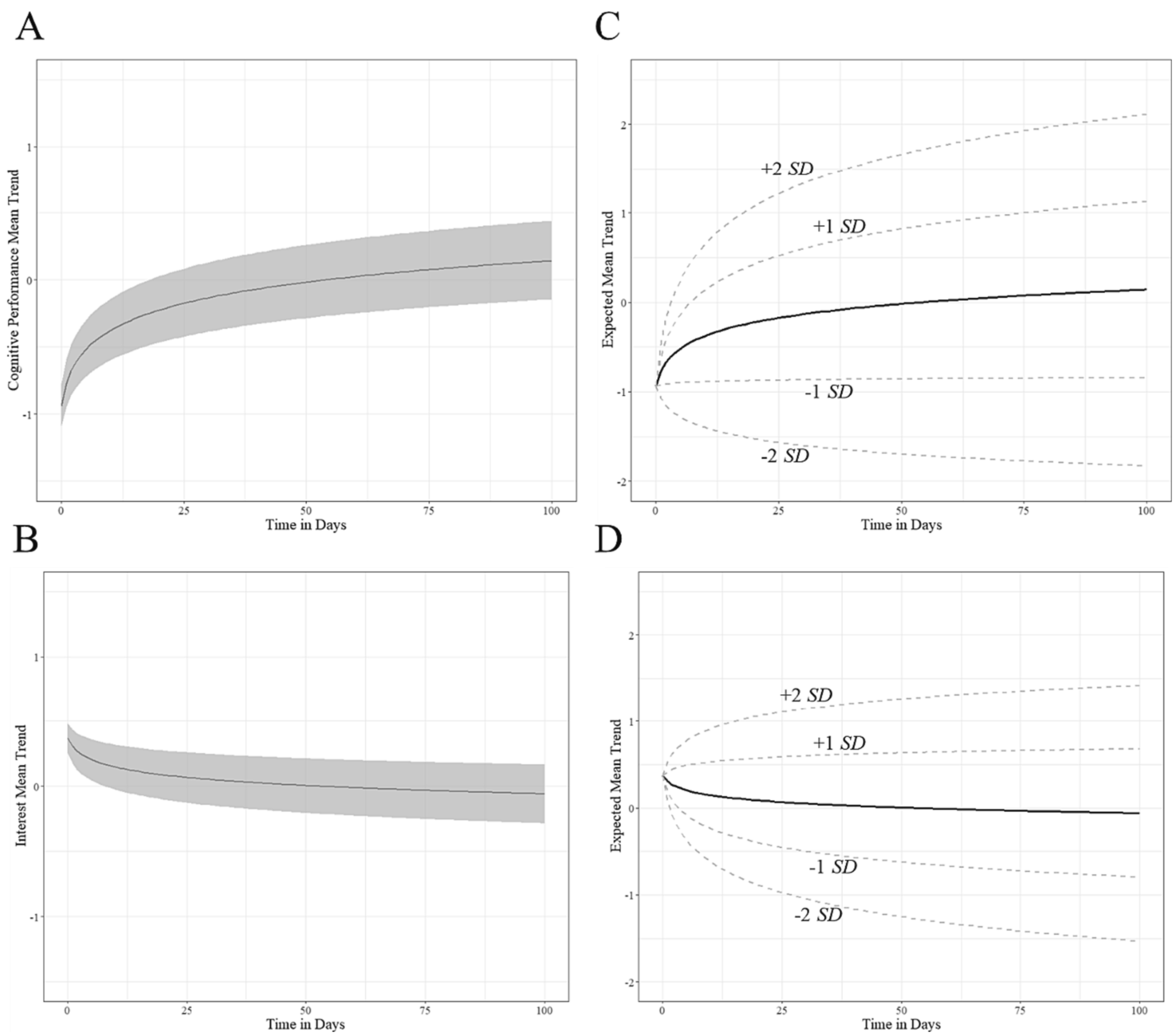

Fig. 2. Model-implied expected mean trajectories for cognitive ability and interest trait development (A and B) and respective between-person differences (C and D).

are user-friendly wrappers for these software programs.

5. Learning from data: an empirical illustration using the COGITO data

For our empirical illustration, we use data from the COGITO ("Cognition Ergodicity") study, which was conducted at the Max Planck Institute for Human Development in Berlin, Germany (Schmiedek et al., 2010a, Schmiedek et al., 2010b).

5.1. Measures

As an operationalization for intellectual investment personality, we used the item "interested" from the PANAS (Watson et al., 1988). The item was translated into German from the English version, which reads "How much do you feel interested at the moment?" The response format was an 8-point Likert scale ranging from 0 (*does not apply at all*) to 7 (*applies very well*). Cognitive performance was operationalized as the percent correct score from four blocks of a spatial *n*-back task (3-back spatial), a measure of working memory (see Schmiedek et al., 2010a, for details). In this task, a sequence of 39 black dots appeared at varying locations in a 4 × 4 grid, and participants were supposed to recognize whether each dot was in the same position as the dot three steps earlier in the sequence or not. Both measures were z-standardized before data analysis.

5.2. Sample and design

The main data acquisition phase was 2006–2007. During this period, 101 younger (20–31 years; 51 % female) and 103 older (65–80 years; 50 % female) adults repeatedly worked on cognitive tasks at approximately 100 measurement occasions. The study design was an unequal-interval individualized design because participants themselves could choose their times of measurement within some boundaries. Thus, participants took 114 to 251 days to complete the study (see Figure 5 in the article by Hecht et al., 2019). Since the participants determined the measurement days themselves, there were no missing values in the true sense, but unequal measurement intervals between measurement occasions resulted. In this study, we only use data from participants who completed the longitudinal study. However, the dropout rate was overall rather low (i.e., below 7 %; see, Schmiedek et al., 2010a).

5.3. Analysis and model

The empirical estimands described above are part of Lohmann et al.,'s (2022, 2023) continuous-time modeling approach. The only ingredient that needs to be made concrete is the expected shape of the trajectory curve. For our empirical illustration, cognitive performance and interest were both modeled using logarithmic shapes. The estimation was conducted with the R package ctsem version 3.7.6 (Driver & Voelkle, 2021). Annotated R code for estimating the employed

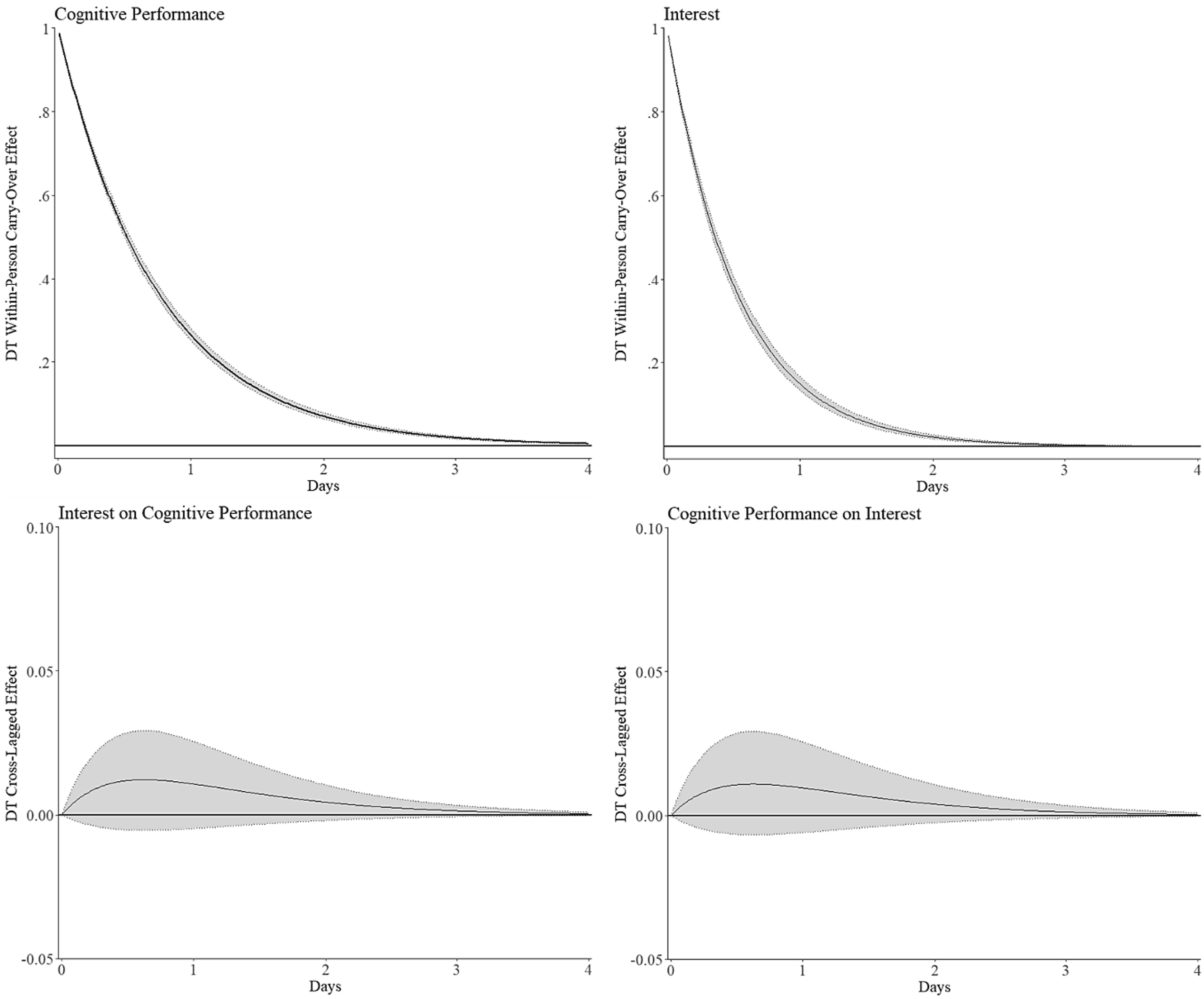

Fig. 3. Model-implied within-person reciprocal relationship between cognitive ability and interest as unfolding over time.

continuous-time model is provided in the Online Supplementary Material at OSF (https://osf.io/c5sna/).

Modeling between-person differences in dynamics, as included in our theory, places particularly high demands on the data. More concretely, both the number of within-person repeated measurements T and the number of subjects N should be large (see, e.g., Jongerling et al., 2015; Lohmann et al., 2023; Schultzberg & Muthén, 2018) for in depth discussions, simulations, and recommendations). Because the data used in our empirical application included a relatively small N, we decided to include only random effects for trends but not dynamics[3] (Fig. 1). This still allowed considering interindividual differences in trends and capturing the within-person dynamics of primary interest.

6. Results

Table S1 in the Appendix provides estimates, standard errors, and 95 % confidence intervals for all model parameters. Our focus here lies on the empirical estimands of interest and the model-implied trend curves, and thus, we will not interpret the other parameters in detail. Fig. 2 displays the trend curves, including mean trends with 95 % confidence bands in the left panels, and "*SD* plots" in the right panels, which showcase the between-person variability in the trend curves. The cognitive performance (Panel A) shows mean logarithmic growth, whereas interest (Panel B) shows mean logarithmic decline but in a smaller absolute magnitude than cognitive performance. The presence of spread-out lines for ±1 and ±2 standard deviations in Panels C and D suggests that there is considerable between-person variability in the shape of the growth curve for both cognitive performance and interest.

Fig. 3 presents the derived discrete-time parameter plots for the autoregressive effects (upper panels) and cross-lagged coefficients (lower panels) with 95 % confidence bands. The autoregressive effects for both cognitive performance and interest gradually diminished after approximately 2 days. Still, the autoregressive effect for interest dissipated slightly more quickly than that of cognitive performance. The interval-dependent cross-lagged coefficients, which are our empirical estimands of interest, were essential zero. This result implies that cognitive performance and interest states were not temporally coupled or predictive of each other in our specific empirical example. In other words, if state interest was exceptionally high or low on one day, it did not have a predictive effect on the subsequent level of cognitive

[3] An attempt to fit the more complex model including the random effects for the dynamic model parameters resulted in convergence issues and implausible estimates (e.g., Zitzmann et al., 2022). Simulation studies for CTMs with random dynamics are still a research gap, and the data requirements are largely unknown.

performance states. Similarly, high or low levels of cognitive performance states did not appear to predict a particular level of interest at a later time. These findings suggest that, contrary to theoretical expectations, cognitive performance and interest operated independently of each other and did not demonstrate a significant temporal relationship, at least not in the current empirical illustration.

7. Discussion

Personality and cognitive abilities are principal classes of individual differences, and both encompass important predictors of a range of life outcomes (e.g., in the domains of health, educational and occupational success, and interpersonal relations; Stanek & Ones, 2023; Roberts et al., 2007). Hence, for over 100 years, researchers have been interested in the connections between personality and cognitive abilities. A prominent perspective on how cognitive abilities and specific personality traits (i.e., intellectual investment personality traits) mutually reinforce each other has been provided by Intellectual Investment Trait Theory (e.g., Ackerman, 1996; Chamorro-Premuzic & Furnham, 2004; von Stumm & Ackerman, 2013; Ziegler et al., 2012; Ziegler et al., 2015). Nonetheless, despite its impact, Intellectual Investment Trait Theory has several blind spots. For example, it relied chiefly on the study of longer term between-person associations while neglecting the intricate and conceptually relevant interplay between momentary expressions of cognitive performance and personality.

The first aim of this article was therefore to advance theory on the interface between personality and cognitive abilities by introducing Dynamic Intellectual Investment Trait and State Theory to the field. Dynamic Intellectual Investment Trait and State Theory is a logical yet innovative extension of Investment Trait Theory, but the dynamic theory expands the range of phenomena that can be explained. It focuses on dynamic within-person reciprocal relationships between cognitive performance states and intellectual investment personality states. Dynamic Intellectual Investment Trait and State Theory integrates (but separates) within-person dynamics and developmental trajectories, as states are conceptualized as deviations from trait-like developmental trends in investment personality traits and cognitive abilities (Wrzus & Roberts, 2017). In Dynamic Intellectual Investment Trait Theory, reciprocities between cognitive performance states and intellectual investment personality states are captured by the situation exploitation and success hypotheses, which also connect Dynamic Intellectual Investment Trait and State Theory with broader dynamic personality theories (e.g., CBFT, WTA, e.g., DeYoung, 2015; Revelle & Condon, 2015) and current conceptions of personality development (e.g., Wrzus & Roberts, 2017). Further, Dynamic Intellectual Investment Trait and State Theory is embedded in a continuous-time framework, representing another novel feature of the theory.

Guided by the premise that only the alignment between personality theories and methodological approaches can build a better science of personality and individual differences, the second aim of our work was to engage in rigorous theory-model matching, and thus, to demonstrate how to precisely map hypotheses of Dynamic Intellectual Investment Trait and State Theory onto a statistical model. Accordingly, we derived the appropriate theoretical and empirical estimands (Lundberg et al., 2021) for investigating Dynamic Intellectual Investment Trait and State Theory's situation exploitation and exploration hypotheses. Based on the estimands, a continuous time latent curve model with structured residuals (CT-LCM-SR) recently proposed by Lohmann et al. (2023), was selected for our empirical illustration. The model disentangles trends and cross-lagged coefficients, incorporates states as deviations from developmental trends, and describes trends and dynamics on a continuous-time scale (Lohmann et al., 2023). Overall, one of the most vexing challenges in (personality) psychology is to ensure the fit between our theories and the arsenal of advanced statistical techniques. The most sophisticated methods provide little value (and even lead to misleading conclusions) if they fail to reflect complex and nuanced theories. Hence, the adopted theory-model mapping approach brings us one step forward in our quest of forging stronger connections between theoretical and statistical models (see also, e.g., Curran et al., 2014). In this regard, it is important to note that we adopted the perspective that a causal relation between X and Y implies a specific temporal order in which Y (the effect) is preceded by X (the cause). In line with this reasoning, we assumed that some time had to pass in order for investment personality states to affect current cognitive performance states (or vice versa). This means that current cognitive performance states at a time point T are influenced by investment personality states at an earlier time point $T - 1$. This notion differs fundamentally from that of a contemporaneous effect according to which causation takes place at a single point in time. Given that our notion of a causal relationship critically depends on the assumption that time has to pass, we did not consider contemporaneous effects to be a meaningful empirical estimand for our Dynamic Intellectual Investment Trait and State Theory. Nevertheless, in other theories and models, contemporaneous effects may be interesting and modeled, for example, with the help of the classical unit fixed effects regression (e.g., Imai & Kim, 2019).

Notwithstanding the contributions our work makes to theory development and theory-model mapping, we did not find support for the situation exploitation and exploration hypotheses in our empirical illustration. The reasons for this finding are difficult to establish but may be linked to the setting and other characteristics of the study from which the data stemmed. Specifically, the study was part of a large research project conducted in the lab. It included many cognitive assessments, which may have decreased the intrinsic valence of "the situation" and counteracted the unfolding of mechanisms underlying situation exploitation and exploration processes. Future research revisiting Dynamic Intellectual Investment Trait and State Theory both in the lab and in everyday real-world contexts (e.g., children playing with an educational app that includes cognitive assessments at home; Behnamnia et al., 2022) can add clarity. Further, measurement issues may have blurred the effects in our empirical illustration. For instance, interest was assessed with a single item. Future studies on Dynamic Intellectual Investment Trait and State Theory employing more comprehensive multiple-item measures, which also comes with the advantage of being able to conduct latent variable modeling, are warranted. Also, future studies on Dynamic Intellectual Investment Trait and State Theory focusing on other intellectual investment trait measures (e.g., intellectual curiosity, Openness, need for cognition, specific interests, typical intellectual engagement, e.g., Jach et al., 2022; Roemer et al., 2020; Staff et al., 2018; Strobel et al., 2019) are needed. In addition, our empirical illustration relied on a sample of German adults from two age groups (see, e.g., Schmiedek et al., 2010a; Schmiedek et al., 2010b), who were recruited (e.g., through newspaper advertisements, flyers, word-of-mouth) to participate in the study. The advertisements were aimed at people who were interested in practicing cognitive tasks for 4–6 days a week for a period of about 6 months (Schmiedek et al., 2010b). It has been argued that the sample was quite representative regarding general cognitive functioning (Schmiedek et al., 2010a); nonetheless, we cannot rule out the possibility that specific characteristics of the current sample may have systematically influenced the findings, and there may still be some restrictions regarding the representativeness of the sample. As a final note, although continuous-time modeling is a valuable descriptive tool and may even be used to "approximate" causal estimators, caution is needed when interpreting results causally. Whether they can be considered causal critically depends on our willingness to accept mostly unrealistic additional assumptions. Specifically, in our model as it stands, it is assumed that results are not affected by time-varying confounding. However, even if some confounders can be controlled for by integrating them into the model, this cannot preclude that there are yet other confounders that have been overlooked. This remains a limitation unless existing causal estimators (Gische & Voelkle, 2022) are adapted to the continuous-time framework.

Furthermore, we want to give an outlook on promising directions and further developments within Dynamic Intellectual Investment Trait and State Theory. First, it is important to reiterate that we were interested in finding out how people function in general (i.e., effects in the average person). Although we did not obtain evidence for general temporal relationships in our empirical illustration, there may still be participants for whom such a relationship in the hypothesized direction held. This heterogeneity of temporal dynamics among persons, which is embedded in our theory extension but could not be investigated because of the high data requirements for modeling random dynamics, may be worth investigating in future research because it can help us understand under which circumstances participants show the hypothesized relationships and, ultimately, to investigate the boundary conditions for Dynamic Intellectual Investment Trait and State Theory. Second, albeit Dynamic Intellectual Investment Trait and State Theory as presented in this article emphasizes shorter term processes, the theory is compatible with longer term development as well. For instance, we propose that a stronger "coupling" between intellectual investment personality states and cognitive performance states (i.e., stronger dynamic reciprocal relations) may give raise to longer term personality and cognitive ability ("trait") development. Further theory and method development is needed to achieve a better theoretical and empirical grip on these pathways. Third, we encourage future studies to take a closer look at the mechanisms that should play a role in the situation exploitation and exploration hypotheses (e.g., feedback, evaluations, emotions) to gain a more thorough and accurate understanding of the mechanisms underlying the reciprocities in Dynamic Intellectual Investment Trait and State Theory. Fourth, for further extensions and refinements of the theory, it may be fruitful to consider commonalities between Dynamic Intellectual Investment Trait and State Theory and principles from existing theories and to engage in intertheoretical integrations (e.g., mutualism, van der Maas et al., 2006, reward-learning framework of knowledge acquisiation, Murayama, 2022, or "classical" motivational theories such as the four-phase model of interest development, Hidi & Renninger, 2006, achievement goal theory, Bardach et al., 2020, and situated expectancy-value theory, Eccles & Wigfield, 2020). As we approach our conclusion, we would like to offer a non-exhaustive set of recommendations for researchers interested in applying dynamic models.

7.1. Recommendations for dynamic modeling and design choices

When contemplating continuous-time models, and dynamic models in general, researchers should carefully consider design features such as the number of persons, the number of time points, and the sampling frequency, including the consideration of whether the sampling frequency should vary within and/or across individuals. Factors like these can impact various aspects, including model convergence, parameter bias, the accuracy of inferences, and statistical power, among others. Due to the relatively recent adoption of continuous-time modeling in psychology, there is a limited body of methods research offering recommendations. Nevertheless, a few pioneering studies have begun to address this gap.

Hecht and Zitzmann (2021a) conducted a study that explored convergence, parameter bias, and coverage rates of parameters from a specific continuous-time model, which could be considered the continuous-time counterpart of a univariate random intercepts cross-lagged panel model, and for a specific design—an unequal interval non-individualized design. They investigated how these aspects were affected by the number of time points and the number of persons. Furthermore, they demonstrated an interesting phenomenon called the "N/T compensation effect." This effect implies that having more persons can compensate for shorter time series, and conversely, having more measurement occasions can compensate for a smaller number of persons. The N/T compensation effect tends to be more effective when there is a higher degree of similarity among individuals, meaning that the intra-class correlation is lower. While the generalizability of Hecht and Zitzmann (2021b) findings is constrained by their focus on a single model and design, their exceptionally clear presentation of results through easily accessible heat maps can serve as a valuable starting point for researchers considering continuous-time modeling.

In another study, Hecht and Zitzmann (2021a) examined how the statistical power of peak cross-lagged effects is influenced by the number of individuals, the number of time points, and, naturally, the effect size. They employed a model that can be regarded as the continuous-time equivalent of a bivariate random intercepts cross-lagged panel model, alongside an unequal interval non-individualized design. Following extensive simulations and the application of machine learning techniques, they developed a prediction formula for the statistical power of peak cross-lagged effects and integrated this formula into an accessible and user-friendly Shiny app, making it readily available for use.

A limited number of studies have delved into design features in conjunction with continuous-time models. Adolf et al. (2021) identified optimal sampling rates that minimize standard errors and offered study planning recommendations. Batra et al., (2023, p. 1) "…recommend researchers use sampling intervals guided by theory about the variable under study, and whenever possible, sample as frequently as possible." Voelkle and Oud (2013, p. 103) showed that "…it can be advantageous to use unequal sampling intervals, in particular when the sampling rate is low." Regarding the individual variation of time interval lengths, Hasl et al. (2023) demonstrated that the precision and recovery of intervention effect estimates improve with individual variation in time intervals.

While research on continuous-time models is relatively limited, there is likely a more extensive body of research focused on their discrete-time counterparts. Although transferability of recommendations from the discrete-time to the continuous-time domain remains uncertain, it can still offer an initial insight into the models and factors that affect estimation performance. If achieving maximal statistical power is a priority, researchers can refer to the article by Hecht et al. (2023) and utilize the associated Shiny app to identify the optimal number of persons and time points (given a fixed budget) for various widely-used discrete-time dynamic models.

Finally, caution is in order when interpreting results from continuous time models causally. This is because in correlational studies, confounding effects of omitted variables likely occur. We thus recommend considering the effects of interest within a causal framework, such as the one by Judea Pearl (Pearl, 2009). For a well-prepared, didactic application of Pearl's DAG-based approach to discrete-time cross-lagged models, we refer readers to the work of Gische et al. (2021). Additionally, researchers may find valuable insights in the existing literature regarding the effectiveness of specific models in addressing unobserved confounding. For example, Lüdtke and Robitzsch (2022) offered a comparative analysis of various models used for estimating cross-lagged effects under a causal inference perspective. In a similar vein, Murayama and Gfrörer (2023) provided insights on handling time-invariant confounders in cross-lagged panel models. Further, in the context of longitudinal models, Rohrer and Murayama (2023) explored the role of within-person data in relation to making causal inferences. However, when the attempt to align the causal theoretical estimand with a causal empirical estimand leads to difficulties or if there is uncertainty about its success, we suggest adopting a cautious approach by employing descriptive language to avoid potentially overstating causal conclusions. This is the approach we have employed in this paper. Ending with a cautionary note, researchers should exercise care when applying the cited recommendations in this subsection, verifying their relevance and appropriateness within their specific context.

7.2. Conclusions

To conclude, we believe that it is an exciting time to conduct research on the interplay between cognitive abilities and personality. We hope that the proposed theory extension Dynamic Intellectual Investment Trait and State Theory and its future developments—matched with the appropriate modeling approaches and well-suited data—can serve as an inspiration for research on cognitive abilities and personality and for research on reciprocities between psychological constructs more generally.

Open Science: We include our analysis code on the Open Science Framework (OSF, https://osf.io/c5sna/). The data analyzed in this study is from the COGITO study and currently not publicly available, but researchers can apply to use the data (https://www.mpib-berlin.mpg.de/1291424/cogito). This study was not pre-registered.

CRediT authorship contribution statement

Lisa Bardach: Conceptualization, Writing – original draft, Writing – review & editing. **Julian Lohmann:** Conceptualization, Writing – review & editing, Formal analysis, Visualization. **Kai T. Horstmann:** Conceptualization, Writing – original draft. **Steffen Zitzmann:** Conceptualization, Writing – original draft, Writing – review & editing. **Martin Hecht:** Conceptualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

Acknowledgement

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jrp.2023.104445.

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