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Understanding child executive functioning through use of the Bornstein specificity principle

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ABSTRACT

A focus on intraindividual change and person-specific pathways is a necessary starting point for *developmental* science inquiries. However, research often relies on ergodicity-based assumptions about group averages and other variable-centered approaches. Using ideas associated with relational developmental systems metatheory, such as the Bornstein Specificity Principle, we re-examine the ergodicity assumption using Executive Functioning (EF) data from the Measures and Methods Across the Developmental Continuum Project. Participants from Grades 4 to 12 (*M* age = 14.60) completed three behavioral EF tasks (i.e., working memory, response inhibition, and cognitive flexibility). The final analytic sample included 64 participants who provided data on 30 measurement occasions. Intraindividual and interindividual EF latent constructs appeared to be different, and we identified a wide range of person-specific EF trajectories. These findings challenge the ergodicity assumption framing variable- and group-oriented approaches to individual development. This study demonstrates the feasibility of collecting intensive longitudinal data to understand youth development on an individual level as an alternative to immediate data aggregation and as means to illuminate the use of the specificity principle in understanding human development and in applications pertinent to enhancing the lives of diverse youth across specific times and places in their specific developmental pathways.

Introduction

Human development involves intraindividual change (Baltes, Reese, & Nesselroade, 1977). However, interindividual (nomothetic or group differential) approaches to measurement, which focus on differences between people, have been the predominant lens through which scientists have sought to understand human development (Emmerich, 1968; Lerner, 2018; Molenaar & Nesselroade, 2014, 2015; Nesselroade & Molenaar, 2010; Rose, 2016). These approaches focus on nomothetic (universally applicable) facets of human development and assume that large-sample statistics (e.g., averages and interindividual differences; Rose, 2016) describe all members of the population equally well. Molenaar (Molenaar, 2004; Molenaar, 2008; Molenaar & Nesselroade, 2015) noted that the use of such statistics assumes the applicability of the ergodic theorems which, in effect, require that group statistics apply equally to all intraindividual changes in a sample.

The ergodicity assumption is rarely tested (e.g., see Brose, Schmiedek, Lövdén, Molenaar, & Lindenberger, 2010), especially when individuals are only measured once or sparsely in longitudinal studies. Although person-centered and clustering analyses, such as growth mixture modeling, may be conducted to determine differences in subgroup scores, such analyses do not fully capture intraindividual change pathways (trajectories) of each participant in a sample. However, idiographic (i.e., person-specific) approaches to research design and data

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analysis allow for the identification of such trajectories (Nesselroade & Molenaar, 2010). If such developmental specificity were found to be ubiquitous in studies of important facets of human development, the implications for theory, methodology, and application in developmental and educational science would be substantial. As Bornstein (2017, 2019), Molenaar and Nesselroade (2015), and Rose (2016) have noted, developmental and educational science would need to shift "figure and ground" in research and program evaluation: Analysis of individual pathways would need to have primacy over immediate aggregation of data across participants in the service of statistical inferences about a population.

Shifting the focus from ergodicity-dependent group-based conclusions to individual-specific pathways has importance for applications in settings (e.g., involving educational assessment or employment) where decisions are made about individuals based on their deviation from averages on a single (or sparsely assessed) standardized test. As both Bornstein and Putnick (2019) and Rose (2016) have noted, each individual has a developmental range of competency and no average score can adequately represent the breadth of abilities or potential of an individual. When averages (norms) are established for populations not reflecting the specific individual and cultural attributes of an individual, and when there is an absence of assessment of the attributes of a specific youth across multiple times and in different contexts (Bornstein, 2019), as may often be the case in regard to educational assessments of youth of color (Farrington, 2020), inaccurate characterizations of the capabilities of a young person may result (Winthrop, 2018).

Accordingly, and especially for youth who face challenges caused by racism, poverty, or other adversities (Cantor et al., in press; Cantor, Osher, Berg, Steyer, & Rose, 2019), acknowledging the potential person-specific pathways to thriving can enhance the precision of understanding development. Such precision can prevent educators, employers, or other evaluators of a specific young person's abilities and potentials from comparing the individual to norms that may not apply to them or making inferences about them based on a single or very limited assessment of their behavior (Cantor et al., in press; Spencer, in press).

The absence of assessments of youth specificity across time and place of attributes integral to their thriving in settings such as educational ones was, therefore, the basis of the present research. That is, the purpose of the present research was to use person-specific measures, designs, and analyses to assess whether a core attribute of positive academic achievement development during childhood and adolescence—executive functioning (EF; e.g., Blair, Ursache, Greenberg, & Vernon-Feagans, 2015; Mills et al., 2018)—conforms to the ergodicity assumption or if evidence suggests that group statistics do not adequately represent individual EF developmental pathways in youth. Using concepts drawn from relational development systems (RDS; Overton, 2015) metatheory and the Specificity Principle advanced by Bornstein (2017, 2019), we report findings derived from use of person-specific measures of EF among samples of elementary through high-school youth (approximate ages 5/6 to 18 years) participating in an intensive longitudinal study (i.e., a study with densely sampled repeated measurements; Bolger & Laurenceau, 2013; Lerner, 2018). Because of the issues that we have noted regarding the absence of information about youth specificity across time and place being of a particular moment for youth of color in the United States (e.g., Cantor et al., in press; Farrington, 2020; Winthrop, 2018), this research focused particularly on youth of color.

Interrogating the ergodicity assumption

A metatheory is a theory of theories (Lerner, 2018; Overton, 2015) that specifies the key concepts that should be included in any theory (or model). RDS metatheory emphasizes that models of human development should focus on integrated, holistic, and systematically and mutually influential (i.e., dynamic) relations among all levels of organization in the ecology of human development. These coacting levels include biological, cognitive, emotional, and behavioral attributes of the person, social relationships, community, and cultural institutions, and the physical ecology—all changing interdependently across history (time) (e.g., Molenaar, 2014; Overton, 2015; Witherington, 2014, 2015). These coactions (typically represented as individual⇔context relations) involve specific individuals and mean that self-construction (autopoiesis) and agency should be part of any theory of development. In addition, these coactions mean that, as Overton (2015) explained, development is *embodied*; that is, each person's behavior and development are an integration of *specific* and mutually influential (i.e., dynamic) relations between a specific individual and their unique biological, psychological, and social/cultural context. In other words, individual⇔context coaction means that a person is always a physical, psychological/behavioral, and sociocultural entity (Overton, 2015; Raeff, 2016). The specifics of the times and places of these coactions for each person create fundamental, idiographic facets of each person's life course (Elder Jr., 1998; Elder, Shanahan, & Jennings, 2015).

These idiographic features of development are the reason why the Specificity Principle (Bornstein, 2017, 2019) is of particular value in describing, explaining, and optimizing development for diverse youth. The principle leads researchers to treat person-specific coactions as the starting point of thinking about the process of youth development. Bornstein (2017, p. 5) noted that:

In life-span human development, some characteristics and experiences have broad implications. Where one is born, how much education one accrues, one's gender, as examples, doubtless have pervasive consequences over the life course. Even so, as life proceeds, advantages and disadvantages cumulate to heterogeneity—so much so that variability and therefore specificity are inevitable. That is, the life-span development of specific characteristics in specific individuals is affected by specific experiences in specific ways at specific times—this is the specificity principle … The specificity principle advances a theory that is particularistic in nature."

In short, and consistent with the holistic and integrated character of the developmental system depicted in all RDS-based conceptions of development, the Specificity Principle (Bornstein, 2017, 2019) indicates that specific contextual conditions of specific people occurring at specific times moderate specific domains of development (e.g., physiological, psychological, sociocultural) through specific processes of individual⇔context coaction. Thus, because of the fundamental specificity of human development, an important implication exists for studying the unfolding of any developmental construct: No one route to the development of any construct exists, no one developmental pathway (e.g., stage sequence) is universal, either within or across time, and no experience (e.g., a challenging or traumatic event or an educational program aimed at enhancing learning or thriving) can be expected to have identical impacts on all youth (Cantor et al., 2019).

The Specificity Principle (Bornstein, 2017, 2019) provides an approach to understanding development within the frame of RDS-based models. The science of individuality, as discussed by Rose (2016), is constituted by the RDS-based Specificity Principle together with concepts and associated methodologies linked to dynamic systems models (e.g., Fischer & Bidell, 2006; Mascolo & Bidell, 2020; Mascolo & Fischer, 2015; Molenaar, Lerner, & Newell, 2014). For instance, methodological approaches, such as dynamic growth modeling, enable the precise examination of sources of variation within nonlinear systems of hierarchical complexity, particularly when such methods address intersectionality (e.g., Fischer & Kennedy, 1997; Hartelman, van der Maas, & Molenaar, 1998; Singer & Willett, 2003; van Geert, 1991); findings from such methods do not necessarily generalize to all human beings or all members of a group (Fischer & Bidell, 2006; Ghavami, Katsiaficas, & Rogers, 2016; Wachs, 2015).

In contrast to ergodic-based approaches to development, which seek to identify universal (nomothetic) attributes of development, the Specificity Principle, embedded in these literatures about dynamic systems concepts and methods, leads researchers and program evaluators to ask multi-part questions that explore the impact of specific experiences on the development of individual youth. For instance, researchers might explore:

- What specific features of thriving emerge for specific youth?
- How do specific life events or contextual conditions moderate specific features of thriving?
- What specific set of individual psychological, behavioral, and demographic characteristics is most influential on developmental outcomes?
- What specific family, school, faith community, neighborhood, national, cultural, and physical ecological variables shape a specific developmental pathway?
- What are the specific points in ontogenetic development (i.e., periods of life)?
- How do historical periods, for example, before, during, or after a major, non-normative historical event (such as the Great Depression of the 1930s, World War II, 1939–1945, or the COVID-19 pandemic; Ettekal & Agans, 2020), alter specific developmental pathways?

Asking such Specificity Principle-based questions enables developmental scientists to understand the specific individual and contextual bases of person-specific pathways across childhood and adolescence. Addressing such questions may advance knowledge of individual⇔context relations that constitute basic processes of life-span human development. Accordingly, in the present study, we used questions derived from the Specificity Principle to interrogate the ergodicity assumption within research analyzing person-specific measurement of EF in samples from across the elementary school through high-school grade range (Chase et al., 2020; Yu et al., 2020).

Understanding EF through an idiographic lens

EF describes complex cognitive functioning that enables reasoning, problem-solving, and goal-directed thinking and assists in regulating attention, emotions, and behaviors according to external demands (Blair & Ursache, 2011; Miyake et al., 2000; Miyake & Friedman, 2012). EF is a key aspect of child and adolescent development, providing a foundation for higher-level self-regulatory processes and predicting academic achievement and overall adjustment (Blair & Ursache, 2011; Cantor et al., 2019; Lantrip, Isquith, Koven, Welsh, & Roth, 2016; Osher, Cantor, Berg, Steyer, & Rose, 2020; Stafford-Brizard, 2016).

Researchers typically describe EF as composed of three related but separable components (Best & Miller, 2010; Garon, Bryson, & Smith, 2008; Miyake et al., 2000): *Working memory (updating)*, the ability to hold and manipulate information in one's mind; *Response inhibition (inhibitory control)*, withholding or restraining a motor response; and *Cognitive flexibility (set shifting)*, the ability to shift focus according to different task demands (Garon et al., 2008; Miyake et al., 2000). These components display both unity and diversity in factor analytic models, with substantial correlations between components and a common factor on which all variables load ("Common EF") as well as "nested" latent variables that capture updating-specific and shifting-specific components (Miyake & Friedman, 2012). In nomothetical developmental studies, EF appears to exhibit a unitary structure in the early years of life and then differentiates into separate components when children are between 3 and 5 years old (Caughy, Mills, Owen, & Hurst, 2013; Wiebe et al., 2011). In turn, EF develops rapidly during the preschool years (ages 2/3 to 5 years) and continues developing into adolescence (Best & Miller, 2010; Diamond, 2006; Garon et al., 2008; Montroy, Bowles, Skibbe, McClelland, & Morrison, 2016; Yu, Caughy, Smith, Oshri, & Owen, 2020).

These findings of EF development mainly derive from studies that infer intraindividual structure and development using sparse measurement or interindividual differences in cross-sectional designs. This approach depicts the structure and development of EF from an ergodic perspective that focuses on averages. However, the assumption that EF develops according to an ergodic process has not been empirically tested in samples of children and adolescents. Cross-sectional or longitudinal studies involving sparsely sampled data cannot adequately identify intraindividual developmental changes in EF components or whether latent structure and developmental patterns are equivalent on interindividual and intraindividual levels. To understand EF through an idiographic lens, intraindividual variability (i.e., fluctuation) must be captured at shorter time intervals than have been used in existing longitudinal research. Therefore, a major gap in knowledge about a key facet of successful academic achievement exists (Cantor et al., in press; Stafford-Brizard, 2016).

To better identify intraindividual trajectories and variabilities of EF, research designs need to increase the number of measurement occasions for each participant (Hooker, Nesselroade, Nesselroade, & Lerner, 1987; Molenaar, 2008, 2014; Molenaar & Nesselroade, 2012, 2014, 2015). Therefore, repeated measures (i.e., longitudinal and intensive) designs are needed, and the division of the timescale must be consistent with a theory-based understanding of person-specific change in the developmental process being studied (Collins, 2006; Lerner, Schwartz, & Phelps, 2009). Although such methods have not been used to assess the person-specific development of EF among children and adolescents, evidence from studies with adults involving the Working memory component of EF supports meaningful intraindividual variation in EF trajectories and thus does not support ergodicity assumptions (e.g., Brose et al., 2010; Brose, Schmiedek, Lövdén, & Lindenberger, 2012). In addition, the ergodicity assumption is not applicable in studies of affect and other cognitive functioning (Brose, Voelkle, Lövdén, Lindenberger, & Schmiedek, 2015; Grandy, Lindenberger, & Werkle-Bergner, 2017; Haqiqatkhah & Tuerlinckx, 2019; Ram et al., 2005). Moreover, studies with adults have demonstrated that EF may fluctuate day to day (Schmiedek, Lövdén, & Lindenberger, 2009) and can vary due to different contexts (Blair & Raver, 2012; Blair & Ursache, 2011; Katzir, Eyal, Meiran, & Kessler, 2010; Lindström & Bohlin, 2012; Oaksford, Morris, Grainger, & Williams, 1996; Phillips, Bull, Adams, & Fraser, 2002). If such variation also existed among children and adolescents, the implications for theory and application to education and youth development programs would be significant. In short, then, the importance of ascertaining whether ergodicity of specificity characterizes the development of EF among children and adolescents led to the present research.

The present study

The Bornstein (2017, 2019) Specificity Principle asserts that each individual follows a unique developmental trajectory and that each trajectory is marked by unique and meaningful features specific to that person. Using this conceptual frame, we examined differences between interindividual and intraindividual EF structures through person-specific analyses of intraindividual variability (e.g., Molenaar & Nesselroade, 2015; Ram & Grimm, 2015; von Eye, Bergman, & Hsieh, 2015). We aimed to answer the following questions: 1. Does the ergodicity assumption adequately represent EF structures of children and adolescents? In other words, is the latent structure of EF drawn from interindividual data equivalent to intraindividual EF latent structures? 2. Are individual fluctuations and variabilities representable by the group fluctuation and variability? and 3. Are individual-specific trajectories and variabilities meaningful?

Method

Participants and procedure

We recruited a convenience sample of participants from elementary, middle, and high school classrooms across the United States, including communities in Boston, MA, Austin, TX, O'Donnell, TX, and

Washington, DC. Sampling occurred as a multi-stage process in which the research team first contacted schools and classroom teachers. Once a teacher agreed to participate, all students in their classroom were offered the opportunity to participate. Participants' assent and parental consent were both obtained before data collection. A total of 108 participants from Grades 4 to 12 were enrolled.

Intraindividual variability in EF was assessed within an intensive longitudinal design, which is defined by Bolger and Laurenceau (2013) as involving a large number of repeated measurements within a short period of time. The present study involved 30 repeated measurement occasions across 81 and 170 days (M = 104.75 days, SD = 20.35). Participants used an online platform to complete measures between one and four times per week, primarily in the classroom during regular school instruction.[1] In keeping with current best practices for stable process data analysis (e.g., McNeish & Hamaker, 2019), we restricted our analytic sample to participants who completed at least 30 measurement occasions to meaningfully analyze and interpret intra-individual variation. Accordingly, the final analytic sample included 64 participants who provided data on 30 measurement occasions. The ages of the participants ranged from 9.75 to 18.08 years old (M = 14.60, SD = 2.53), with 15.6% of participants in elementary school, 21.9% in middle school, and 62.5% in high school. Most participants were boys (60.9%). As noted above, this study sought to over-sample youth of color, and 32.8% of the participants were Black/African American, 48.4% were Latinx, 10.9% were mixed race, and 4.7% were European American.

Measures

Each time participants logged onto an online platform to participate, they were instructed to complete the Dimensional Change Card Sort (DCCS) task, the Flanker task, and the Common Object Ordering (COO) task in a randomized order. Because data collection required youth to stay engaged throughout repeated measurements, each task had more than one version to avoid boredom and fatigue effects.

Cognitive flexibility

Cognitive flexibility was measured using a short, self-administered version of the DCCS task (Zelazo et al., 2013). In each DCCS trial, participants were asked to select between two cards that matched a target object either by color or shape. Before each trial, participants were told which dimension (color or shape) they should match on. There were five color and five shape trials, and the order of the trials was randomized for each participant on each measurement occasion. In Version 1, the shapes were stars and circles, and the colors were blue and red. In Version 2, the shapes were triangles and squares, and the colors were purple and green. At each measurement occasion, a version was randomly assigned to the participant. Color sets were chosen to ensure that individuals with any type of achromatopsia would be able to easily distinguish the colors. In addition, for each set, one color had higher brightness so that even individuals with total color blindness would still be able to see a clear visual difference between the colors.

When participants first started the tasks, there were options for "Instruction" and "Start the Game." First, the word "shape" or "color" appeared on the screen for 3000 msec, indicating the matching criterion for the current trial. Then, the word disappeared, and the target object and the two option objects appeared on the screen. Participants used keyboard arrow keys to match the cards. Pressing the left arrow key selected the left card to match the target object, and pressing the right key selected the right card to match the target object. After the participant pressed an arrow key, the screen provided feedback on whether the match was correct or incorrect (see Fig. 1(a)).

Accuracy and reaction time were measured for each trial. Before score computation, trials with reaction times shorter than 200 msec were defined as anticipatory responses and excluded (Finch, Garcia, Sulik, & Obradović, 2019; Miyake et al., 2000; Sulik & Obradović, 2018). Trials with reaction times more than 3 standard deviations above the individual's daily mean or longer than 3000 msec indicated loss of attention and were excluded (Zelazo et al., 2013). After excluding off-task trials (i.e., trials excluded due to the above criteria), an accuracy score was computed as the percentage of correct trials multiplied by the number of total trials. Accuracy scores ranged between 0 and 10. Median reaction time was calculated using only correct response trials (Zelazo et al., 2013). Because neither accuracy nor median reaction time can fully represent cognitive flexibility due to a potential accuracy-reaction time trade-off (Zelazo et al., 2013), both accuracy and reaction times were used to compute the overall DCCS score. Median reaction time was first log-transformed and then algebraically rescaled to range between 0 and 10, with longer reaction times transformed to lower scores (reaction time score = 30.35–8.77 × lg(median reaction time)). To ensure accuracy was the priority of the scoring process, participants with less than an 80% accuracy rate kept their accuracy score as the final DCCS score. In contrast, participants with 80% or higher accuracy rate were scored using the sum of accuracy and reaction time score as the final DCCS score (Zelazo et al., 2013). The range of DCCS final score was 0 to 20.

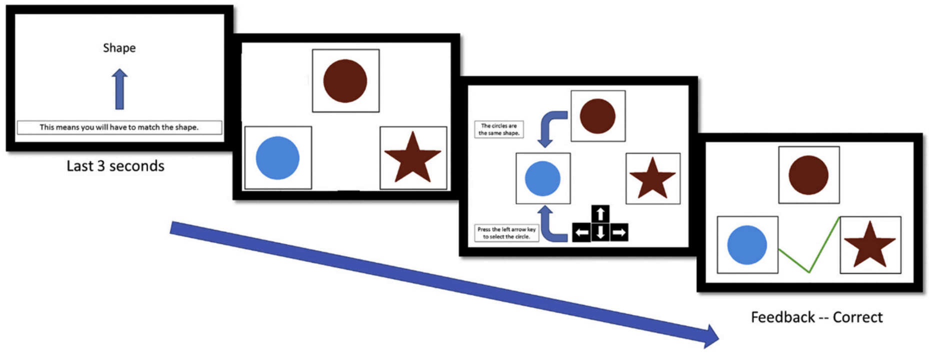
Response inhibition

Response inhibition was measured via a short, self-administered version of the Flanker task (Huizinga, Dolan, & van Der Molen, 2006). Participants were asked to identify the direction of the target object in the center of a row of objects (i.e., Version 1 used fish; Version 2 used birds; see Fig. 1(b)). When the target object was facing the same way as the rest of the objects, the trial was defined as congruent. When the target object faced the opposite way as the rest of the objects, the trial was defined as incongruent. In addition, the row of objects moved across the screen; on congruent trials motion was in the same direction as the target object, on incongruent trials motion was in the opposite direction as the target.

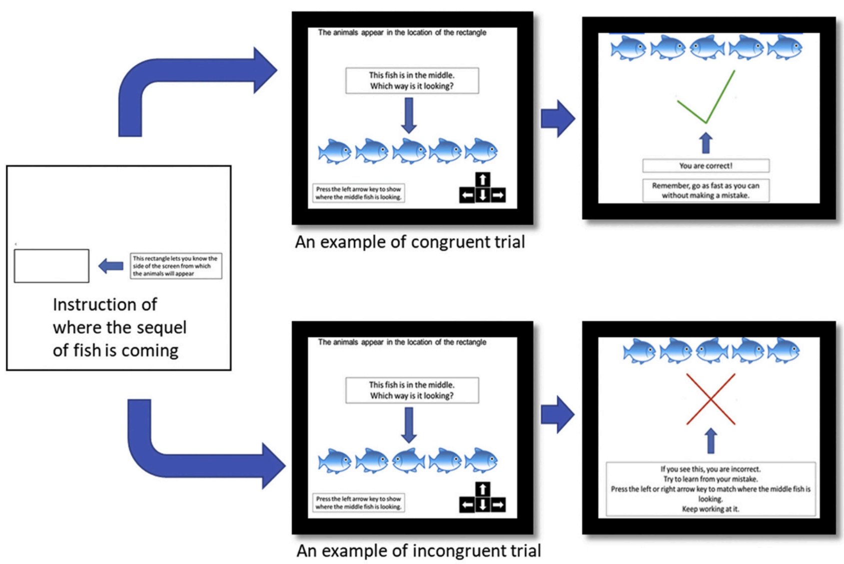
The Flanker task consisted of 12 trials: 6 congruent and 6 incongruent trials. Pre-piloting of this task showed that it was extremely easy for participants, leading to ceiling effects. Therefore, we added movement to increase prepotent responses because motion is a highly salient characteristic of visual scenes (e.g., Smith & Abram, 2018). Rather than appearing in the center of the screen, the stimuli appeared either to the left or the right and then moved across the screen (the image would loop back to its starting position and move again if it reached the edge of the screen). The image always moved in the direction the distractor images pointed; therefore, for congruent trials it moved in the same direction as the answer, and for incongruent trials it moved in the opposite direction. We found the expected response pattern in the Flanker task: A paired t-test revealed that participants had slower reaction times to incongruent trials than to congruent trials, $t(1824) = 13.30, p < .01$; d = 0.20. All but 3 participants had a faster response to congruent trials than incongruent trials based on their median reaction times across 30 measurement occasions.

To quantify inhibitory control, median reaction time and mean accuracy were computed for incongruent trials and congruent trials, respectively. Like the short DCCS task, trials with reaction times shorter than 200 msec and trials with reaction times more than 3 daily standard deviations above the child's daily mean or 3000 msec were considered to indicate loss of attention and were excluded. In line with the NIH

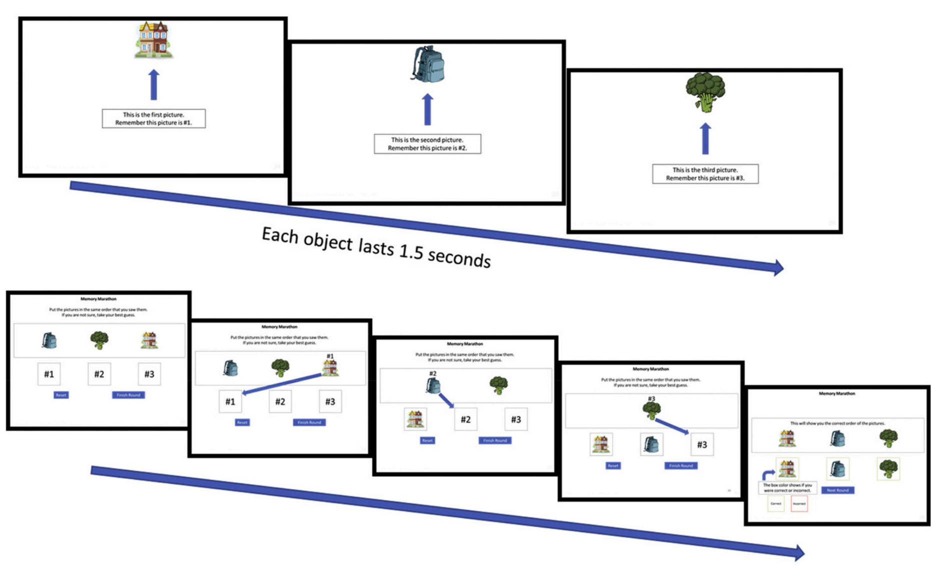
[1] Data collection for our study spanned fall 2019 to spring 2020 and thus included observations both prior and subsequent to the COVID-19 pandemic. As a result, a small portion of measurement occasions (47 out of 1920 observations, or 2.4%) were completed at home rather than in the classroom. However, all other aspects of the participant experience were persevered throughout this transition, including the task presentation, administration method, and testing platform. Thus, we do not anticipate the change in setting to have substantially affected participant responses or the pattern of results observed.



(a) Demonstration of Computer-Based Short DCCS Task (Version 1)



(b) Demonstration of Computer-Based Short Flanker Task (Version 1)



(c) Demonstration of COO procedure Trial 1

Fig. 1. Demonstration of the three remote executive functioning tasks.

Toolbox, the accuracy score is based on the total of congruent and incongruent accurate trials (Zelazo et al., 2013). Using the same scoring strategy from the NIH Toolbox, the reaction time score was only based on the incongruent trials (Reaction time score = 36.10–10.43 × lg (median reaction time of correct incongruent trials)). When the accuracy rate fell below 80%, the accuracy score was the final score. When the accuracy rate was 80% or above, the final score was the sum of accuracy and reaction time scores. The range of final inhibition scores was 0 to 24.

Working memory

Working memory was measured by the common object ordering (COO) task. During the task, participants were shown a series of pictures of common objects (e.g., banana, backpack) and then asked to recall the order of the pictures. The task consisted of 4 trials. Participants were asked to order 3 pictures in Trial 1, 5 pictures in Trial 2, 7 pictures in Trial 3, and 9 pictures in Trial 4. For illustration, see Fig. 1(c). Unlike the DCCS and Flanker tasks, the participants were not asked to order the objects as fast as possible because the ordering process is likely to be impacted by characteristics of the device being used.

In COO, only accuracy was assessed, not reaction time. Due to increasing difficulty for each trial, different weights were given to the four trials. The working memory score was computed as 1 × correct objects in Trial 1 + 2 × correct objects in Trial 2 + 3 × correct objects in Trial 3 + 4 × correct objects in Trial 4. At the end of each trial, feedback on correctness was provided. The score ranged from 0 to 70.

Demographic variables

Child age, gender, and race-ethnicity information were collected in the consent form.

Data analysis plan

Data analysis was divided into three parts. Prior to answering the research questions, we first examined whether past findings of interindividual correlations among EF tasks (e.g., Miyake et al., 2000; Miyake & Friedman, 2012) were present in our data set. We started by creating intraindividual means and standard deviations of the three EF tasks across 30 measurement occasions for the 64 participants. Then, descriptive results (i.e., interindividual *M*s and *SD*s) and bivariate correlations were computed to test whether the scores of cognitive flexibility (DCCS), response inhibition (Flanker), and working memory (COO) were correlated, as demonstrated by previous between-person studies. Age differences were also investigated by computing bivariate correlations, *M*s, and *SD*s.

Second, to answer the first research question, we examined differences in the interindividual and intraindividual correlations among the three EF tasks as an initial step in attempting to assess whether differences existed in the latent structure of EF. The current data set can be described as 30 interindividual studies with 64 participants in each study. It can also be defined as 64 intraindividual studies with 30 measurement occasions within each person. If the ergodicity assumption is met for the common EF factor, the distribution of correlations between EF tasks in 30 interindividual studies and 64 intraindividual studies should be similar (Brose et al., 2010).

Third, to further answer the first research question and answer the second and third research questions, a dynamic structural equation model (DSEM) was conducted to examine differences between intraindividual and interindividual EF latent structures and person-specific variabilities. The DSEM is a combination of multiple existing analytical methods, including multilevel modeling, time-series analyses, and structural equation modeling (Asparouhov, Hamaker, & Muthén, 2017; Hamaker, Asparouhov, Brose, Schmiedek, & Muthén, 2018). To answer the first research question, we compared the intraindividual and interindividual latent structures of EF using the DSEM, which includes a two-level dynamic factor analysis (DFA) and two-level time-series components. These features allowed us to examine the structure and variability of EF within-persons (Level 1) and between-persons (Level 2). Allowing the three EF scores to load on a common EF latent factor, the two-level DFA component in DSEM then allows the three EF latent factor loadings to differ across individuals and to account for observation dependency; this procedure constitutes an idiographic approach (Asparouhov et al., 2017; Molenaar, 1985; Zhang & Nesselroade, 2007). In addition, the between-person (Level 2) factor loadings are conceptually similar to the latent structures from traditional nomothetic analyses (e.g., one-level confirmatory factor analysis).

The same DSEM also included the time-series analyses of each participant; these analyses were aimed at answering the second research question. The EF latent score was estimated for each individual on each day, and a two-level time series analysis on the EF latent level was conducted. Such a two-level time series model allowed variability parameters to differ from individual to individual (Jongerling, Laurenceau, & Hamaker, 2015). Thus, two kinds of variability parameters were examined: time-irrelevant amplitude of fluctuation and time-relevant temporal dependency (Wang, Hamaker, & Bergeman, 2012). Amplitude of fluctuation was indexed by log-transformed intraindividual variance (log(iSD^2) in the *Variance Model* (e.g., Mun et al., 2019; Nesselroade & Salthouse, 2004; Ram et al., 2005; Wang et al., 2012). Temporal dependency was indexed by autoregression (AR) in the *AR Model*, which is the association between the performance of yesterday and today.

Regarding AR, the time-interval has a significant impact on the interpretation (Mun et al., 2019). Because the smallest time interval between two measurement occasions was 1 day, we used 1 day as the time-interval for autocorrelation (AR(1)). Therefore, AR(1) represents how much "today's EF latent score" is predicted by the "EF latent score a day ago." Days when participants did not complete EF tasks were treated as missing data. AR(1) was estimated in the AR Model together with innovation variance, which is the residual intraindividual variance after an amount of variance is explained by previous performance.

In the estimation of the two models, detrending the data is needed when there is systematic change over time (McNeish & Hamaker, 2019; Wang et al., 2012). In the time-series analyses, variability parameters are assumed to be stationary and there should be no systematic change. However, systematic change can still happen, for example, due to practice or fatigue effects over the course of data collection (Schmiedek, Lövdén, & Lindenberger, 2010; Wang et al., 2012). Failing to account for a systematic trend over the course of data collection could result in a dramatic increase in intraindividual variance and invalid autocorrelations (Wang et al., 2012). There is no consensus on a single best detrending method. For a straightforward interpretation, we accounted for a potential linear trend (i.e., Slope) in the data by including an estimation of slope in the Variance Model and AR Model (McNeish & Hamaker, 2019; Mun et al., 2019; Wang et al., 2012).

Bayesian estimation with a Markov Chain Monte Carlo (MCMC) algorithm was used in *Mplus* for DSEM, treating missing data as unknown parameters (Asparouhov et al., 2017). This method is suitable to deal with a large amount of missing data (e.g., more than 80%) when using a fine grid of time segments (i.e., smaller time intervals between measurement occasions; Asparouhov et al., 2017; de Haan-Rietdijk, Gottman, Bergman, & Hamaker, 2016). At the same time, Bayesian MCMC estimation yields a distribution of parameters (McNeish & Hamaker, 2019). Instead of reporting a *p* value, a 95% credible interval (CrI) is more appropriate for DSEM. If zero is included in the 95% CrI, the parameter can be interpreted as "non-significant". For the purpose of a straightforward interpretation, the median of the parameter distribution and the 95% CrI are reported in the results.

We answered the last research question by using the variability parameters generated by the DSEM models, individual age and gender were then linked to person-specific Log(iSD^2), Slope, AR(1), and innovation variance to examine the meaningfulness of person-specific variabilities.

Results

Prior to answering the three questions addressed in this research, we conducted descriptive statistics and correlations among age and gender and EF. *M*s and *SD*s are presented in Table 1. Intraindividual *SD*s were all above zero, indicating that the data collection successfully captured some amount of intraindividual variability. Based on the bivariate correlations, the intraindividual *M*s of the three tasks were strongly correlated with each other, which is consistent with findings from nomothetic studies (e.g., Miyake et al., 2000; Miyake & Friedman, 2012).

Moreover, age was positively associated with all three *M* scores. This finding is consistent with prior research that finds EF improves between middle childhood and adolescence (Best & Miller, 2010). Age was also negatively associated with DCCS and Flanker *SD*s, indicating that older participants performed more consistently on the two tasks. In short, based on the findings from interindividual analysis, the intensively collected data demonstrated similar patterns to sparsely collected data if approached with a similar analytical method.

Distributions of interindividual and intraindividual EF correlations

The first research question asked whether the interindividual and intraindividual EF structures were equivalent. Accordingly, we computed the distributions of 30 interindividual and 64 intraindividual EF correlations are shown in Fig. 2. The interindividual distribution (across 30 occasions) had a higher *M* and smaller *SD* than the intraindividual distribution (across 64 participants) of EF correlations (see Table 2). For all three correlations (DCCS & Flanker, DCCS & COO, Flanker & COO), interindividual correlations ranged between 0.2 and 0.8, which is consistent with previous nomothetic findings regarding a common EF factor (Miyake & Friedman, 2012). However, intraindividual correlations demonstrated a much larger range from moderate negative correlations to positive correlations. Such different distributions of interindividual and intraindividual correlations were the first piece of evidence to indicate that interindividual and intraindividual EF structures are different, and the interindividual EF latent structure might not represent the EF latent structure for a specific individual.

Dynamic structural equation modeling: Contrasting intraindividual and interindividual findings

The DSEM models provided additional data that answered the first research question and addressed the second and third questions. Table 3 includes the results of two DSEM models. Model 1 (the Variance Model) only included the log-transformed intraindividual variance (Log(iSD^2)) and Slope, and Model 2 (the AR model) included AR(1), Slope, and the innovation variance. The factor loadings on within-person and between-person levels were almost identical in the two DSEM models. The between-person (interindividual) level factor loadings are conceptually similar to current nomothetic findings of EF, showing that cognitive flexibility, response inhibition, and working memory could load on one common EF factor (Miyake & Friedman, 2012).

However, the within-person (intraindividual) loadings are very different from the interindividual loadings. In particular, DCCS and COO loaded weakly, on average, across individuals. Although there is no direct statistical test, it appeared that between-level and within-level latent structures were different, suggesting that intraindividual EF structure may not be well-characterized by interindividual EF frameworks. This finding is the second piece of evidence that interindividual and interindividual EF structures were different in response to the first research question. The two-level DSEM model further demonstrated inconsistency with the ergodicity assumption in EF. Between-level and within-level latent structures were not commensurate with group-based EF findings.

To answer the second research question, the two DSEM models also generated person-specific Log(iSD^2), AR(1), Slope, and Innovation variance. The distribution of the medians of the individual-specific variability parameters is shown in Fig. 3, in which participants demonstrated very different patterns of variability. Thus, the answer to the second research question is that individual-specific trajectories cannot be represented by a group trajectory. Using MCMC imputed daily median EF latent scores, three participants' time-series analyses were intentionally selected to illustrate different person-specific trajectories. Their line graphs are shown in Fig. 4, and their AR(1) and innovation variance were included for reference. The autoregressive (AR) parameter may explain individual differences in the pattern of fluctuation over time. An AR parameter closer to 1 indicates more carry-over effects from the previous performance as well as a wider range of fluctuations, whereas an AR parameter closer to 0 indicates less temporal dependency as current performance is not predicted by previous performance (Jongerling et al., 2015). Of the three participants, Participant 1's AR(1) score was farthest from zero, and this participant had the largest fluctuations over time. Participant 2, whose AR(1) score was closer to 0, demonstrated low temporal dependency and more random fluctuations. Innovation variance indicates the total variance of each performance (Jongerling et al., 2015). The larger the innovation variance, the more performance variability may be observed. Participant 1 had the highest innovation variance score, which was observed in the amount of variation among each of his temporal EF performances as well. Fig. 4 demonstrates that all three participants had person-specific variability in their EF performance over time.

To answer the third research question and investigate the meaningfulness of person-specific variabilities, correlations between gender and age and four variability parameters were investigated (see Table 4). Although gender was not associated with intraindividual variability, older participants demonstrated smaller intraindividual variance and innovation variance than younger participants. Moreover, older participants demonstrated smaller AR(1), implying that older participants showed less temporal dependency, that is older participants'

Table 1
Descriptive statistics and correlations of participant demographics and EF Ms and SDs.

		Min.	*Max.*	*M*	*SD*	1	2	3	4	5	6	7	8
1	Gender	–	–	–	–								
2	Age	9.75	18.08	14.60	2.53	0.24							
3	Total days	81.00	170.00	104.75	20.35	0.08	−0.17						
4	DCCS *M*	5.29	16.18	12.44	2.20	−0.06	0.43**	−0.26*					
5	DCCS *SD*	0.59	6.44	2.60	1.31	−0.24	−0.29*	0.16	−0.61**				
6	Flanker *M*	8.08	20.15	16.73	2.04	−0.21	0.44**	−0.14	0.87**	−0.40**			
7	Flanker *SD*	0.57	6.12	1.99	1.26	−0.05	−0.28*	0.06	−0.50**	0.62**	−0.60**		
8	COO *M*	12.14	67.62	40.36	14.46	−0.07	0.34**	−0.38**	0.69**	−0.47**	0.65**	−0.54**	
9	COO *SD*	4.60	23.88	13.45	4.03	0.00	−0.03	0.30*	−0.10	0.35**	0.06	0.05	−0.19

Note. Gender was coded as 1 = boy, 2 = girl. DCCS = The Short Dimensional Change Card Sort. COO = Common Object Ordering.
* $p < .05$.
** $p < .01$.

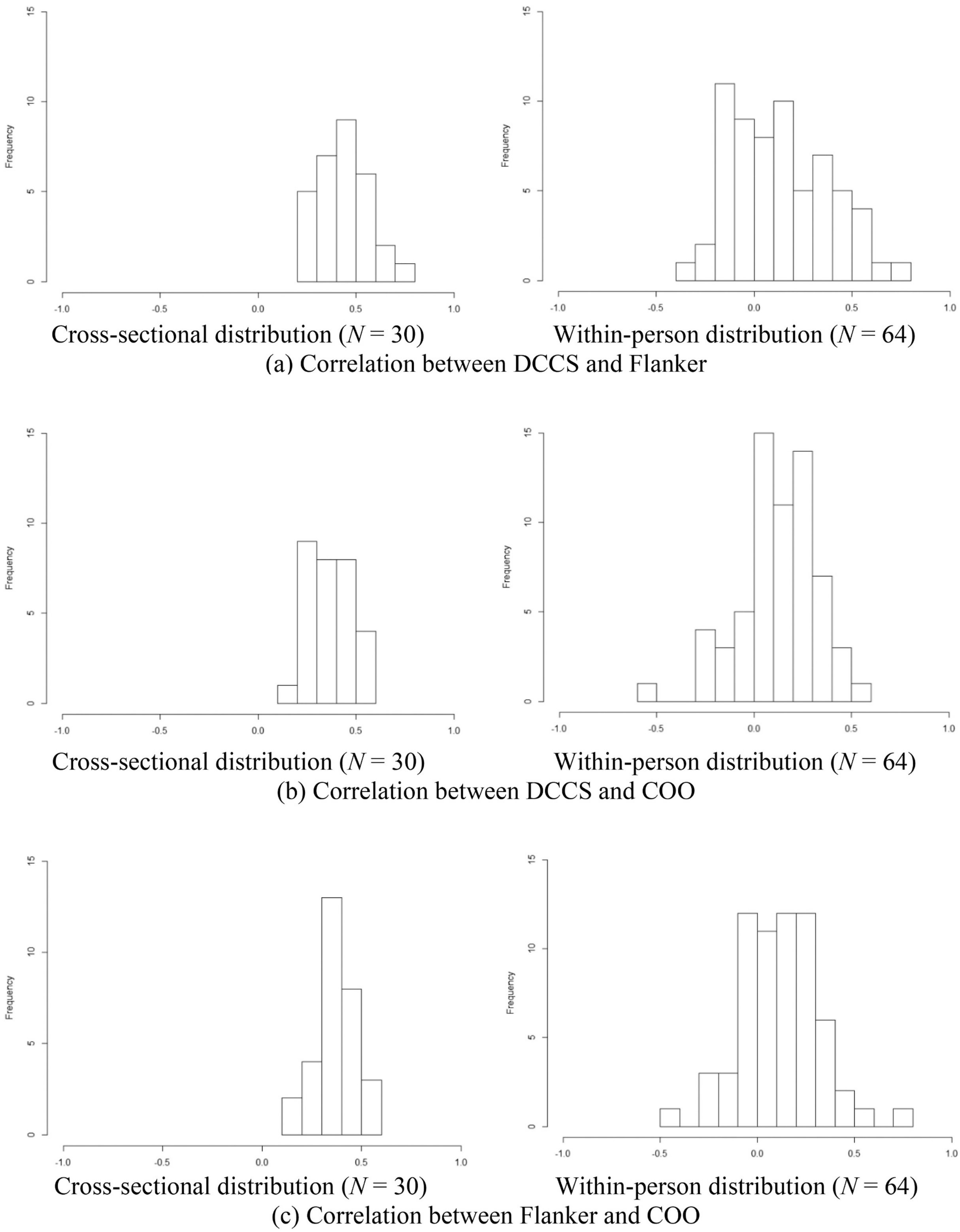


Fig. 2. Distributions of Interindividual (cross-sectional) and intraindividual (within-person) EF correlations. The x-axis is the correlation coefficient and the y-axis is the frequency of the correlation.

performance on a specific day was less dependent on their previous day's performance compared to their younger counterparts. The developmental difference in variabilities suggested to us that the person-specific trajectories were meaningful.

Discussion

Contemporary developmental science documents that every individual has a developmental range of competency and, as well, no one score, and no average score, can adequately represent the breadth of abilities or potential of an individual across time and place (e.g.,

Table 2
Descriptive statistics and cross-sectional and intraindividual bivariate correlations.

	DCCS & Flanker	DCCS & COO	Flanker & COO
Cross-sectional (across 30 occasions)			
*M*r	0.44	0.36	0.37
SD	0.13	0.11	0.10
N	30	30	30
Intraindividual (across 64 participants)			
*M*r	0.13	0.12	0.12
SD	0.25	0.20	0.20
N	64	64	64

Note. DCCS = The Short Dimensional Change Card Sort. COO = Common Object Ordering.

Table 3
Standardized coefficients for factor loadings and variability parameters in two DSEM models.

	Model 1 (Variance Model)	Model 2 (AR Model)
	β [*CrI*]	β [*CrI*]
Within-person (mean across individuals)		
EF factor loading		
DCCS	0.25[0.23, 0.28]	0.24[0.22, 0.28]
Flanker	0.84[0.77, 0.89]	0.80[0.74, 0.86]
COO	0.09[0.05, 0.13]	0.09[0.04, 0.13]
Log(iSD^2)/Innovation variance	0.87[0.83, 0.91]	−0.75[−1.06, −0.42]
Slope	0.11[0.06, 0.16]	0.03[−0.28, 0.34]
AR(1)	–	−0.30[−0.87, 0.14]
Between-person		
EF factor loading		
DCCS	0.95[0.86, 1.00]	0.95[0.86, 1.00]
Flanker	0.91[0.79, 0.98]	0.91[0.80, 0.98]
COO	0.73[0.55, 0.85]	0.73[0.56, 0.85]
Model Fit		
Deviance (DIC)	29,824.52	30,125.70
Estimated Number of Parameters (pD)	1419.89	1408.68

Bornstein & Putnick, 2019; Rose, 2016). When such individuality is not understood or assessed, the capacities and potential of diverse youth, and arguably in particular youth of color, may not be able to be adequately identified in key contexts of importance for their achievement and thriving (e.g., educational or employment settings; e.g., Cantor et al., in press; Farrington, 2020; Winthrop, 2018).

The present research is predicated on the belief that scholarship illuminating the use of the Specificity Principle (Bornstein, 2017, 2019) can address these issues in important ways. Indeed, in the present research, we assessed whether ideas about developmental specificity could serve as a lens to counter the key methodological ideas associated with the use of statistical methods that rationalize ignoring meaningful variation about individual change. That is, the Specificity Principle (Bornstein, 2017, 2019) stands in clear contrast with the ergodicity assumption (e.g., see Brose et al., 2010). Specificity in human development means that nomothetic approaches to developmental analysis cannot alone suffice to account for the structure and function of individual pathways across the life span. As Allport (1968, p. 68) famously stated, "Whatever individuality is, it is not the residual ragbag left over after general dimensions have been exhausted."

Specificity also means that interindividual differences in scores for variables are not equivalent to intraindividual change in a person's score for a variable across the individual's life span. As such, the average for a group cannot represent the meaningful developmental pathway of any person. In short, our findings did not provide support for the ergodicity assumption.

We found different distributions of 30 interindividual correlations and 64 intraindividual correlations among three EF tasks, as well as different interindividual and intraindividual latent structures of EF in the DSEM models. Therefore, the answer to the first research question is that interindividual EF structure is not equivalent to intraindividual EF latent structures; the data in support of our answer challenge the ergodicity assumption in nomothetic studies. Moreover, participants showed person-specific variabilities, and therefore the answer to the second research question is that individual fluctuations and variabilities are not represented by the group fluctuation and variability. Older participants showed less amplitude of fluctuation and less temporal dependency on the EF latent level. In response to the third research question, such a developmental difference indicated that individual-specific trajectories and variabilities were, at least partially, meaningful. Although our sample was composed of volunteer participants, we believe that the consistency of these results across the number of participants we studied and the number of times of measurement used to assess them support our contention that the ergodicity assumption was usefully tested and found wanting.

Linked to RDS-based ideas that underscore the fundamental role of specific individual⇔context relations in constituting the fundamental process of human development across the life span, this research used the Bornstein Specificity Principle to frame our person-specific study of executive functioning, which is a key building block of successful academic achievement and life attainments (Cantor et al., in press; Stafford-Brizard, 2016). In the past, variable-centered research on EF conducted among adults has not interrogated the ergodicity assumption (but see Brose et al., 2010), and we, therefore, examined whether research that assessed person-specific pathways of EF development among children and adolescents would provide support for ergodicity. Our findings did not provide such support.

Relying on nomothetic, variable-centered methods that focus on group averages and, often, cross-sectional designs, many studies have supported diversity and unity in EF development (Caughy et al., 2013; Garon et al., 2008; Miyake et al., 2000; Miyake & Friedman, 2012; Wiebe et al., 2011). This work suggests that three widely used components of EF (cognitive flexibility, response inhibition, and working memory) are able to be differentiated but, as well, are interrelated (Garon et al., 2008; Miyake et al., 2000; Miyake & Friedman, 2012). However, the methods we used for interrogating ergodicity provide evidence that such group-level findings do not necessarily hold for the specific individuals. The unity/diversity framework of EF may not apply to all individuals or, perhaps, to all developmental populations. Future studies should further explore the relevance of the unity/diversity framework for understanding EF in specific individuals and across development.

The intraindividual correlations among the three EF scores varied from moderately negative to strongly positive, and within-person and between-person factor loadings varied sufficiently to imply that the latent structure drawn from group-based data may not be equivalent to the latent EF structure at the intraindividual level. Of course, our findings of the presence of meaningful, person-specific intraindividual structures do not mean that previous nomothetic findings are mistaken. Reflecting Kluckhohn and Murray (1948) assertion that each human is simultaneously like all other humans, like only some other humans, and like no other human, we also found that interindividual analyses of our data are consistent with previous EF studies that focused on averages and interindividual differences in EF scores.

Therefore, interindividual studies remain important parts of the set of investigations useful for addressing specific questions about human development as, for instance, questions about group (e.g., cohort) differences. However, the work we report here indicates that studies of interindividual differences and/or studies of group averages are not

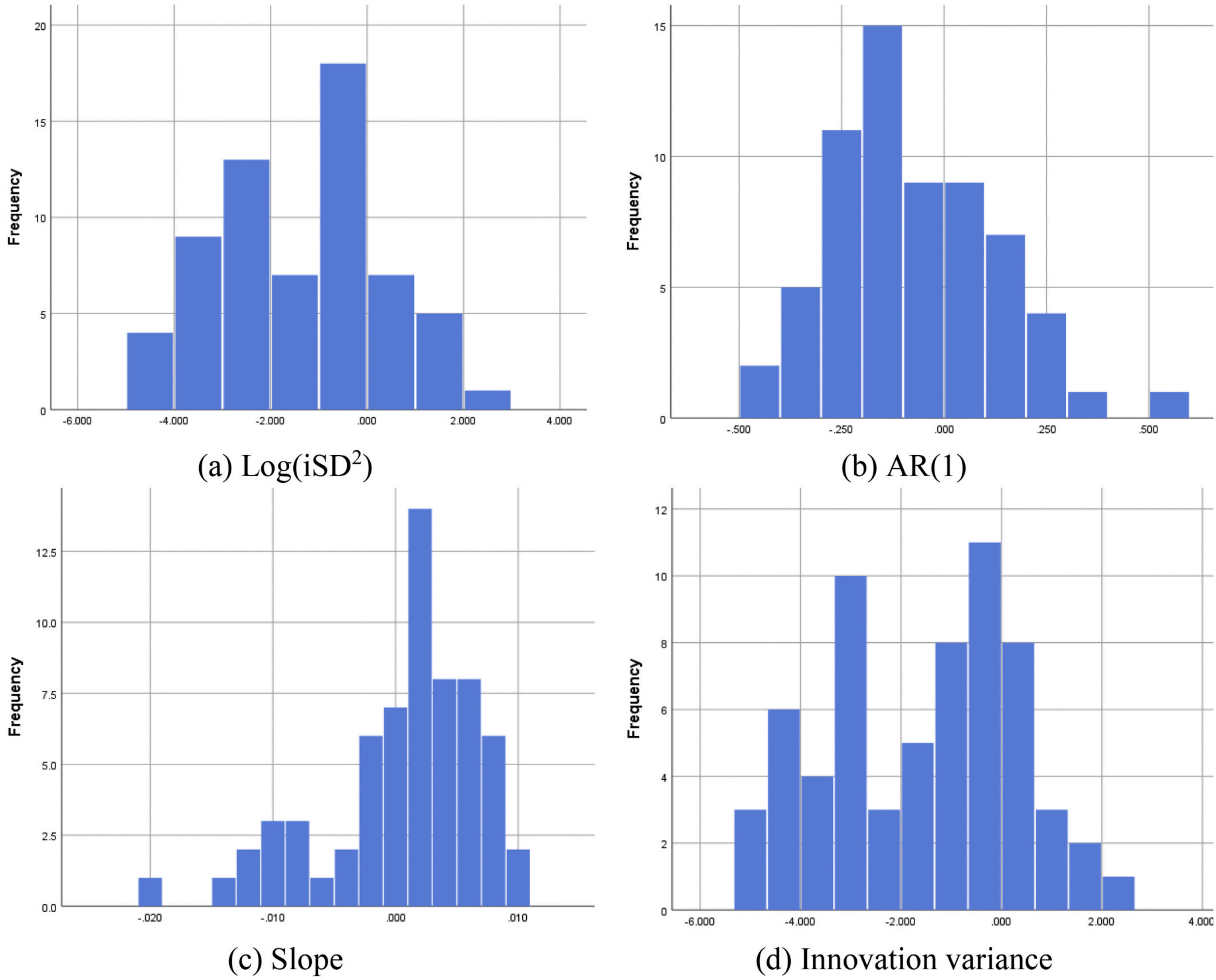


Fig. 3. Distribution of the person-specific variability parameters.

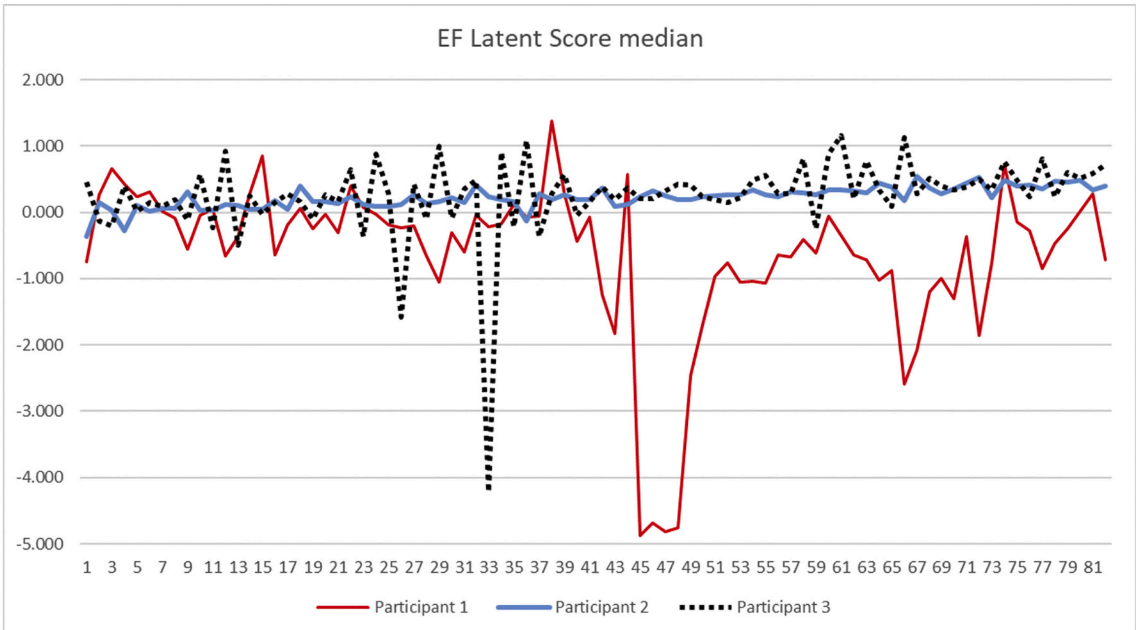
equivalent to studies of intraindividual change. As such, the ergodicity assumption may not always be an appropriate general framework for conducting developmental science (Molenaar, 2008; Molenaar & Nesselroade, 2014, 2015; Nesselroade & Molenaar, 2010; Rose, 2016). Indeed, as Rose et al. (2013, p. 152) explained, most studies conducted within the field of developmental science proceed by first aggregating data across individuals. However:

> By analyzing statistical averages, not individuals, these models provide descriptions about global regularities in everything from cancer… to cognition…. However, we argue that the value of such models ultimately depends on whether they apply to individuals; after all, a science of the group is a poor substitute for a true science of the individual. Traditional models often assume that insights about the population automatically apply to all individuals…. This assumption is simple, it is understandable, and it is necessary to justify the use of averages to understand individuals. However, it is also wrong!

Indeed, the multilevel time-series components of the DSEM demonstrated a wide range of EF interindividual variabilities. We found developmental differences in intraindividual variabilities, implying that intraindividual variabilities may contain valuable information. Such findings are consistent with the Bornstein Specificity Principle, as development involves specific, intraindividual changes in specific domains (Baltes et al., 1977; Bornstein, 2017; Lerner, 2012, 2018). The person-specific variabilities in EF could be a result of individual-specific experiences at the specific time they took the tasks.

Strengths and limitations

To our knowledge, this article reports the first study using DSEM to explore person-specific intraindividual variability and interindividual differences in intraindividual variability in EF among elementary through high school youth. The study used a sample of a wide and unevenly distributed developmental range because of the constrained timeframe. Although a small non-representative sample was used in this research, and the DSEM included many "missing data points" because of uneven and sparse time intervals between measurement occasions, this research offers a new understanding of the development of EF, a core attribute for positive youth development and academic success, using an idiographic approach framed by the RDS-based Specificity Principle. Future studies could include larger samples and intensive measures of developmental contexts, such as classroom environments, teacher behaviors, parent behaviors, and out-of-school times. Linking changing contexts to intraindividual variability will allow developmental scientists to best understand how development unfolds in real-time in



Participant 1
- Log(iSD^2) = 1.24
- AR(1) = .38
- Slope = -.01
- Innovation variance = .74

Participant 2
- Log(iSD^2) = -2.57
- AR(1) = -.13
- Slope = .01
- Innovation variance = -2.79

Participant 3
- Log(iSD^2) = -.07
- AR(1) = -.19
- Slope = .01
- Innovation variance = .05

Fig. 4. Time-series graph of three participants.

Table 4
Bivariate correlations between variability parameters and individual characteristics.

		1	2	3	4	5
1	Age					
2	Gender	0.24				
3	Log(iSD^2) median	−0.26*	0.10			
4	AR(1) median	−0.46**	0.12	0.62**		
5	Slope median	0.17	0.01	−0.44**	−0.26*	
6	Innovation variance median	−0.27*	0.11	0.99**	0.63**	−0.42**

* $p < .05$.
** $p < .01$.

ecologically valid settings of child and adolescent development.

The present research also demonstrated the feasibility of remotely collecting intensive longitudinal data from elementary through high school students. Even without using all of the person-specific data analytic tools available to developmental science researchers (e.g., see Molenaar et al., 2014; Molenaar & Nesselroade, 2015; Ram & Grimm, 2015; von Eye et al., 2015), our analysis of intensive longitudinal data revealed essential evidence about the specificity of intraindividual change in regard to within- and between-person variance and person-specific variabilities. With more intraindividual measurement occasions, we could include covariates and use more complex models to expand on idiographic and interindividual findings.

Conclusions

Intraindividual methods, especially those framed by RDS-based conceptions such as the Specificity Principle, enhance measurement, research design, and data analysis as used in developmental science complement group-differential or nomothetic methods (Lerner, 2018). For example, the latent structure of EF differed between the intra- and inter-individual levels. Each individual showed person-specific variability patterns. However, all participants exhibited fluctuations in EF performance, and some participants demonstrated similar latent structures and variability. In the context of initial emphasis on the idiographic specificity of intraindividual change, it is possible to determine if and how aggregation to group or nomothetic levels is possible. For example, future studies can use methods of Idiographic Filtering developed by Molenaar and Nesselroade (2015) to examine the possibility of aggregation across individuals.

Using the Bornstein Specificity Principle as a frame for developmental science involves examining relations among specific individuals, specific constructs, specific times in ontogeny and history, and multiple specific levels of context. Understanding these relations may require complex data analytic methods. Nevertheless, the Specificity Principle has the potential to represent a transformational shift for research and application in human development, for typically developing children as well as for children with difficult life experiences caused by racism, poverty, or developing in otherwise challenging contexts (Cantor et al., 2019, in press). Acknowledging person-specific trajectories and variabilities in development is a first step in exploring how challenging and nurturing environments can alter specific functioning from day to day. Understanding specific person⇔context coactions of different youth, whether they are living in adverse or privileged contexts, can enhance the precision of understanding their development. Such precision will prevent researchers from implicitly comparing the development of diverse youth to "norms," and reduce potential ethnic bias in using group-based factors and findings to understand individuals from groups that face challenges (Cantor et al., in press; Spencer, in press).

We encourage researchers to use RDS-Specificity Principles of idiographic methods to approach theoretical and applied questions about youth development. Understanding the bases of person-specific pathways across childhood and adolescence will advance knowledge of individual⇔context relations that constitute basic processes of life-span human development. In turn, such understanding will enable educators and other professionals who serve youth to learn how best to align the specific individual and the key, specific contexts of a young person's life to best promote whole-child development, learning, and thriving (Cantor et al., in press).

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