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Exploring Idiographic Approaches to Children's Executive Function Performance: An Intensive Longitudinal Study

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Abstract: Traditional variable-centered research on executive functions (EFs) often infers intraindividual development using group-based averages. Such a method masks meaningful individuality and involves the fallacy of equating group-level data with person-specific changes. We used an intensive longitudinal design to study idiographic executive function fluctuation among ten boys from Grade 4. Each of the participants completed between 33 and 43 measurement occasions (M = 38.8) across approximately three months. Data were collected remotely using a computerized short version of the Dimensional Change Card Sort task. Multi-group analyses of three participant pairs (Participants 5 and 3, 5 and 2, and 5 and 6) demonstrated that Participant 5 differed from Participants 3 and 2 in different ways but Participants 5 and 6 were similar in all comparisons. Dynamic structural equation modeling demonstrated unique individual trajectories, which were not represented by the trajectory of group-averages. Although more than half of the participants showed a negative association between EFs and inattention, two participants showed a positive association between EF and inattention. This study demonstrated meaningful person-specific trajectories of EFs, suggesting that future study should undertake the analysis of individual development before data-aggregation or generalization from aggregate statistics to individuals.

Keywords: idiographic, executive functions, intensive longitudinal study, person-specific approach

Introduction

Developmental scientists often question when and how often developmental change occurs for specific constructs. To appropriately answer the "when and how" question, one needs to first identify the rate a phenomenon of interest changes within a given individual by adequate repeated measurement occasions (Lerner et al., 2009). Variable-centered analyses that examine group-level differences at one or multiple arbitrarily spaced time intervals (e.g., annual assessments) provide, at best, a rough proxy for developmental research (Lerner et al., 2009). Thus, from the perspective of Allport (e.g., 1937, 1968; but see Hurlburt & Knapp, 2006), development must consider idiographic, person-specific, facets of change as well as subgroup or nomothetic facets.

Idiographic approaches emphasize that the changing individual ⇔ context system is the unit of analysis rather than a synthesis of interindividual differences. For example, Bornstein's (2017) Specificity Principle explains that development is unique to individuals, times, domains, and contexts. Although generalization requires some form of data aggregation, developmental research must use idiographic (i.e., person-specific) methods that acknowledge individuality before data aggregation can proceed meaningfully (e.g., Molenaar, 2008; Molenaar & Nesselroade, 2015; von Eye et al., 2015).

As persuasively presented by Molenaar (2004, 2008), the danger of nomothetic research lies in assuming that intraindividual variations are equivalent across individuals. In other words, one must assume that changes in the average across people are equivalent to changes within each person whose scores were used to compute that average. Idiographic research allows a more contextualized understanding of the individual and can acknowledge the person's previous experiences, learning, and behavior patterns. This approach contrasts with traditional individual differences research, which predicts an individual's behaviors based on the way one behaves relative to group-based averages (Nesselroade & Molenaar, 2010). This approach to developmental analysis may be illuminated through focus on the sample case of executive functioning.

An Idiographic Approach to Executive Functions

Executive functions (EFs) represent a multi-component construct that includes working memory, inhibition, and cognitive flexibility (Best & Miller, 2010; Garon et al., 2008; Miyake et al., 2000; Müller & Kerns, 2015). Working memory is the ability to hold and manipulate information in mind (Best & Miller, 2010; Garon et al., 2008; Miyake et al., 2000). Inhibition involves withholding or restraining a motor response (Best & Miller, 2010; Garon et al., 2008; Miyake et al., 2000). Cognitive flexibility is the ability to shift focus according to different task demands (Garon et al., 2008; Miyake & Friedman, 2012; Miyake et al., 2000). EFs develop in a hierarchical fashion as the result of integrating simpler skills (Fischer & Bidell, 2006; Garon et al., 2008; Mascolo & Fischer, 2015). Cognitive flexibility is the most complex EF component and develops last, building upon working memory and complex inhibition abilities. EFs enable reasoning, problem-solving, and goal-directed thinking and assist in regulating attention, emotions, and behaviors according to external demands (Blair & Ursache, 2011; Miyake & Friedman, 2012; Miyake et al., 2000; Müller & Kerns, 2015; Obradović, 2016), and thereby enable reasoning, problem-solving, and goal-directed thinking. Thus, EFs are key processes that lay the foundation for higher-level self-regulatory processes (Blair & Raver, 2012; Blair & Ursache, 2011; Lantrip et al., 2016; Zelazo & Cunningham, 2007).

Traditional developmental research on EFs often infers intraindividual development using sparsely separated measurement occasions within longitudinal designs (e.g., annual assessments) and group-based averages. Doing so, however, creates an ecological fallacy (Molenaar, 2004) that results in inaccurate scientific findings as well as ineffective policies and interventions (Rose, 2016; Rose et al., 2013). For example, longitudinal studies might measure EFs among a group of preschoolers and then again a year later, and the group average might show a statistically significant upward developmental trend in EFs from early to middle childhood (Garon et al., 2008; Carlson, 2005; Diamond, 2006; Frye et al., 1995; Montroy et al., 2016; Yu et al., 2020). However, these trends do not enable practitioners to say with much certainty that a specific 5-year-old must have a higher level of EFs than any other 4-year-old child due to their specific individual ⇔ context relations.

Despite the fallacy of equating group-level trends with intraindividual change, it is possible to acknowledge specificity while simultaneously appreciating some degree of generalization (Bornstein, 2017). Some phenomena, such as a general improvement in EFs across childhood and adolescence, might be nearly universal. Other aspects of development may only be similar across specific groups of people; for instance, youth with similar socioeconomic backgrounds or those who share a common cultural heritage. For example, specific children may exhibit accelerated EF development during preschool but show a slow improvement into middle childhood. Other children may instead show a low starting point in EFs during preschool but demonstrate faster growth later on (Pacheco et al., 2018; Yu et al., 2020).

As the above examples illustrate, generalizations derived from sparsely sampled longitudinal data points and variable-centered analyses must remain extremely broad. Even within a similar group, there is heterogeneity in EF development that results from person-context coactions that are specific to each individual (Bornstein, 2019). Such specificity is often masked when individual information is aggregated first in variable-centered ways because individuality is often treated as measurement error rather than meaningful information.

Another limitation of existing variable-centered studies lies in the sparse measurement of EFs. Changes in EFs can be conceptually differentiated as directional change versus intraindividual variability (i.e., fluctuation) (Ram & Grimm, 2015). Directional change is usually irreversible and may be manifested at macro timescales (e.g., months, years), whereas fluctuations may occur at micro timescales (e.g., hours, days) and are often temporary and reversible. Studies have documented fluctuations in EF performance at micro timescales, impacted by contextual factors (Blair & Raver, 2012; Blair & Ursache, 2011). Some lab-based experimental studies of EFs suggest that lab-induced affect, such as anxiety or pleasant mood, can lead to changes in EF performance, suggesting that such variation reflects fluctuations in EFs during a short period of time (Katzir et al., 2010; Lindström & Bohlin, 2012; Oaksford et al., 1996; Phillips et al., 2002).

In short, then, ignoring intraindividual variability limits understanding in EF development. Current studies of EFs and their development rely on changes in average EF performance with different developmental periods; however, the nature of EF development may not only reflect the improvement of "level of EFs" but also changes in the level and pattern of intraindividual variability/fluctuation of EFs at a micro timescale. Moreover, when EFs are measured sparsely in longitudinal studies, each individual's performance can be a result of both developmental change and location in micro-time scale fluctuations. Traditional variable-centered approaches cannot account for developmental change and fluctuation separately. Studies of affect and pain fluctuation reveal intraindividual variance that cannot be explained by past performances, suggesting that fluctuation can be explained by other daily experiences, such as mood, sleep, and energy levels (Hamaker et al., 2018; Jongerling et al., 2015; Mun et al., 2019). Attributing a combination of developmental change and fluctuation to developmental changes in longitudinal studies with sparsely separated measurement occasions can lead to inaccurate results and missing information from contextual impact at a micro time scale. Therefore, it is important to capture intraindividual fluctuation in the study of EF development.

The Current Study

The traditional "aggregate-first-then-analyze" approach in studies of EF development masks meaningful individuality. Moreover, developmental scientists know little about the fluctuations in EFs in developing young people. Capturing intraindividual variability via intensive longitudinal design is one way to apply the idiographic approach. This type of design includes many repeated measures of the construct of interest within individuals across a relatively short period of time (Bolger & Laurenceau, 2013). In intensively measured person-specific research, the analytic power is associated with the number of measurement occasions instead of the number of participants (Hooker et al., 1987; Molenaar, 2008, 2014; Molenaar & Nesselroade, 2012, 2014, 2015).

In this paper, we report an exploratory endeavor using an intensive longitudinal design seeking to demonstrate the importance of examining the uniqueness of the individual. This study aimed to answer the following research questions:

(1) Can one individual show meaningful differences in EF fluctuation and directional change from another individual?

(2) Can individual fluctuations and directional changes be adequately represented by whole-group fluctuations?

(3) Are intraindividual variations in EFs meaningful (i.e., associated with another cognitive factor, such as attention level)?

Methods

Participants and Procedure

The current study included a relatively homogenous sample of 10 boys from one Grade 4 classroom in an all-boys elementary school. Participants' IDs, race/ethnicity, and age information is shown in Table 1. The study implemented a two-stage sampling design in which classroom teachers were recruited before individual participants. When a classroom teacher agreed to participate, all children in their classroom were offered the opportunity to take part in the study. Both participant assent and parental consent were obtained before data collection. The EF data were collected via an online platform. Participants were instructed by the classroom teacher to complete an EF task on a computer or a Chromebook in the classroom. The participants completed their first measurement on the same day and were asked to complete the task approximately three times per week; however, the frequencies varied due to school activities, absences, and holidays. The data collection started by the end of the fall semester of 2019 (November) and remained ongoing in spring 2020, despite changes in student educational context because of restrictions associated with the COVID-19 pandemic. Data used in this study were collected between November 2019 and mid-March 2020. Only participants with between 30 and 50 measurement occasions were included in the current study (Mean $N = 38.8$).

Table 1
Demographic Information on Ten Participants

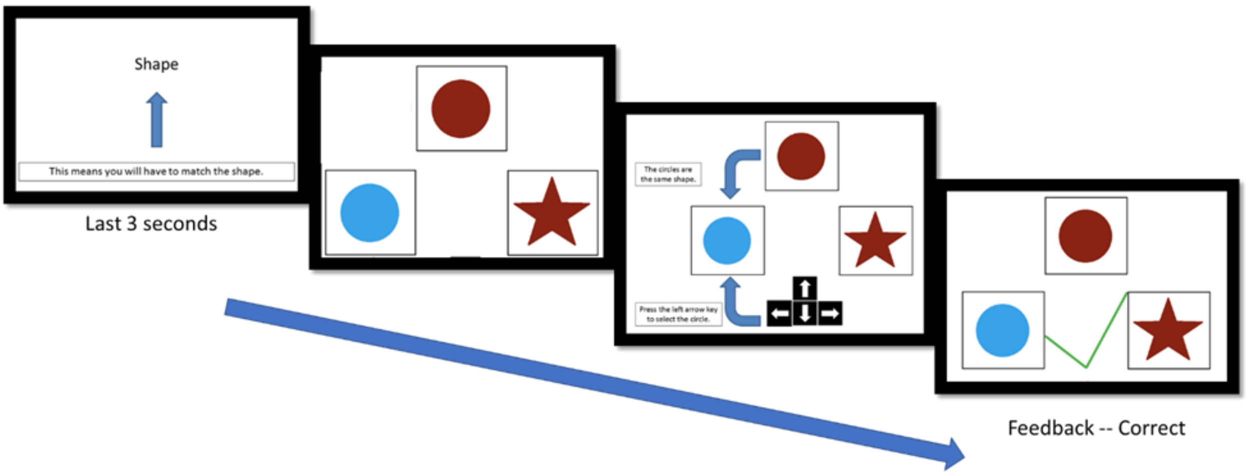
	Race/ethnicity	Age
Participant 1	Hispanic/Latinx	10 years 11 months
Participant 2	Hispanic/Latinx	9 years 9 months
Participant 3	Other (Cape Verdean)	10 years 1 months
Participant 4	Other (Cape Verdean)	Not reported
Participant 5	Not reported	Not reported
Participant 6	Hispanic/Latinx	10 years 1 months
Participant 7	Asian/Black	10 years
Participant 8	Black/Hispanic/Latinx	9 years 5 months
Participant 9	Not reported	Not reported
Participant 10	Not reported	Not reported

Measures

Executive functions and attention. Daily EF performance and attention level were measured using a short version of the Dimensional Change Card Sort (DCCS) task (Zelazo et al., 2013). During the classic DCCS task, a participant is shown two target cards (e.g., a blue rabbit and a red boat) and asked to sort a series of cards according to one dimension (e.g., color) and then another (e.g., shape). The NIH Toolbox DCCS task includes four phases and 50 trials (Zelazo et al., 2013). This existing format of the DCCS EF task may use a good deal of class time and induce participant fatigue when used daily or several times a week. To prevent these effects, we used a truncated version of the task that asked participants to match the pattern either by color or shape as fast as possible. There were five color and five shape trials, with the order of the trials randomized for each measurement occasion. When the participants first started the tasks, there were options for "Instruction" and "Start the Game." At first, the word "shape" or "color" would then appear on the screen for 3000 msec, indicating the matching criterion for the current trial. Then the word would disappear, and the target object and the two option objects would appear on the screen.

Participants were instructed to use the 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 the arrow key, the screen would briefly display feedback on whether the match was correct or incorrect (a green checkmark for correct or a red X for incorrect). At the end of the task, the child's score and average response time were listed on the screen. The procedure is shown in Figure 1.

Figure 1.
Demonstration of Computer-Based Short DCCS Task



The *attention* variable was indexed by "off-task" trials created based on reaction time. Trials with reaction times shorter than 200 msec were defined as anticipatory responses and "off-task" trials (Finch et al., 2019; Miyake et al., 2000; Sulik & Obradović, 2018). Trials with reaction times more than three standard deviations above the child's daily mean or longer than 3000 msec indicated a loss of attention and were also identified as "off-task" trials (Zelazo et al., 2013). For attention level, if the reaction time for a trial was too short or too long according to the criteria, the trial was coded as 1 (i.e., off-task) and otherwise 0. Overall, the off-task performance served as a proximal index for the participant's attention level during the task. Daily latent scores for off-task were created later based on ten trial-level scores in a to-be-described (below) dynamic structural equation model. The daily mean of off-task trials (the number of off-task trials divided by 10) was also created for descriptive purposes. A higher off-task mean indicated a lower level of attention.

EFs were indexed by the accuracy of the short DCCS task. All "off-task" trials were excluded from accuracy coding and treated as missing trials. Accurate trials were then coded as 1, and inaccurate trials were coded as 0. Daily latent accuracy scores were created later based on trial-level scores in the dynamic structural equation model. Average daily accuracy scores were computed as the percentage of correct trials relative to the number of total "on-task" trials multiplied by 10. The accuracy score ranged between 0 and 10. A higher accuracy score indicated a better EF performance.

Time. In order to capture daily variation within individuals, we chose a day as the unit of change (Rioux & Little, 2020). A time variable (i.e., Lag) was coded as the number of days between each assessment and the first measurement occasion. The first measurement occasion was coded as 0 (Lag = 0). The data were collected across 136 days.

Analytical Plan

As a preliminary step, means and standard deviations were first computed for each participant to verify the existence of intraindividual variability for each child. Because of the relatively few measurement occasions available per participant, linear regressions of DCCS accuracy using Lag and off-task mean were conducted for all children, respectively, to preliminarily check whether there was a linear change in accuracy and whether off-task scores co-varied with accuracy. Multi-group analyses were conducted within three pairs of participants to explore whether individual children show significant differences from other individual children for different aspects of EFs. Based on the linear regression[1] results, three pairs of participants were selected to demonstrate three scenarios: when participants differ in level of EF (intercept) and change in EF (the coefficient of Lag), when participants differ in relations between EF and inattention (the coefficient of off-task), and when participants show the same level and change in EF as well as the same relations between EF and inattention. Participant 5 was selected as the reference participant. Analyzing data for this child indicated a non-significant coefficient for Lag but a significant coefficient for off-task. Compared to Participant 5, Participant 2 had a lower intercept, non-significant coefficients for Lag and off-task; Participant 3 had a lower intercept, a significant coefficient of Lag but a non-significant coefficient for off-task; Participant 6 had a similar intercept, a non-significant coefficient of Lag but a significant coefficient of off-task. Participant 5 was thus compared against these three other participants (i.e., Participant 5 vs. 2, Participant 5 vs. 3, & Participant 5 vs. 6). Each parameter between each pair was constrained to be equal across individuals one by one. We then examined differences in the chi-square statistic to test whether there was a significant difference. A significant increase in model fit chi-square indicated a significant difference between the two individuals.

In order to further understand the short-term changes in EFs, a dynamic structural equation model (DSEM) was used to examine individual-specific fluctuations. A DSEM can account for observation dependency and generate person-specific variance and trajectories. DSEM is an extension of N=1 time series analysis to a 2-level (within- and between-individual) multivariate time-series analysis in the SEM framework. An N=1 time series model estimates variation within an individual, emphasizing an idiographic perspective (Nesselroade & Molenaar, 2010). A DSEM model estimates variation individually within multiple participants, treating person-specific variations as random effects in a two-level model (McHeish & Hamaker, 2019). The DSEM can also be understood as a two-level extension of the dynamic factor model analysis (DFA) because the within-individual level of the model applies DFA and allows latent factor loadings to differ across individuals, reflecting idiographic approaches (Asparouhov et al., 2017; Molenaar, 1985; Zhang & Nesselroade, 2007).

Another advantage is that the two-level DFA model can account for measurement errors. In cross-sectional studies, one construct is often measured via multiple related items in order to create a latent factor which estimates the "true score" and the "measurement errors" (e.g., as in confirmatory factor analyses; Kline, 2011). Similar to a cross-sectional confirmatory factor analysis, the DFA can estimate the factor and the measurement errors, as well as accounting for time dependency between observations in an intensive longitudinal context (Asparouhov et al., 2017; Molenaar, 1985; Zhang & Nesselroade, 2007). The DCCS has 10 trials to measure EF, and each trial can be seen as a parallel item for the construct. The DSEM model enabled us to use the observed scores of the ten trials to create a dynamic latent factor for off-task and accuracy at intraindividual and interindividual level. At the within-person level, latent scores for off-task and accuracy were estimated for each individual for each day. Therefore, the fluctuation of EF was observed based on the latent factor after measurement errors were accounted for.

For days when the children did not complete the DCCS task, Bayesian estimation with a Markov Chain Monte Carlo (MCMC) algorithm was used in the 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 (Asparouhov et al., 2017; de Haan-Rietdijk et al., 2016). We then estimated several person-specific parameters to describe person-specific fluctuation: log-transformed intraindividual variance (LogV), autocorrelation (AR), and linear slope based on latent off-task and accuracy factors (Mun et al., 2019). LogV and AR were estimated in two separate models in Mplus. LogV represents the overall variability for off-task and accuracy performance on a daily basis. A higher LogV suggests bigger intraindividual fluctuation. In regard to 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 one day, we used one day as the time-interval for autocorrelation (AR(1)).

DSEM models are considered stationary models, which assume that there is no systematic change in level (e.g., growth or advancement) and fluctuation over time (McNeish & Hamaker, 2019; Wang et al., 2012). Therefore, it is important to remove the systematic change in the data (McNeish & Hamaker, 2019; Wang et al., 2012). Failing to address the systematic trend can lead to inaccurate estimation of the variability measures (Mun et al., 2019). Asparouhov, Hamaker, and Muthen (2017) suggest that by including model predictors that change over time, it is possible to break away from this assumption. Therefore, in both the logV and AR models, time was included as a covariate and the estimation of a linear slope was included to account for the overall trend in off-task and accuracy over time. At the same time, the slope is an index for individuals' directional change over time, which could potentially be due to practice effect on EF tasks (Erkkila et al., 2018; Schmiedek et al., 2010). Because of sparse measurement occasions and limited statistic power, we only estimated a linear slope to the data. The between-level means of LogV, AR(1), and slope were also calculated in the models, which represent the group-based trajectory.

[1]In exploratory analysis with Participant 1 and Participant 2, we found that quadratic, cubic, and cubic spline regressions of Lag were not superior to a linear regression based on adjusted R^2. For simple and clear results, we decided to use linear regression to demonstrate individual uniqueness.

Table 2
Descriptive Results and Unstandardized Coefficient for Multiple Linear Regression

	Descriptive				Regression on Accuracy		
			Accuracy	Off-task	Intercept	Lag	Off-task
	N	Days	*M*(*SD*)	*M*(*SD*)	B	B	B
Participant 1	40	133	8.66(1.54)	.10(.18)	8.339***	.010	-2.629
Participant 2	40	133	7.82(2.09)	.23(.20)	7.420***	.010	-0.845
Participant 3	43	136	8.39(2.17)	.07(.13)	6.356***	.035***	-3.105
Participant 4	36	133	8.12(2.05)	.23(.26)	9.070***	-.001	-2.856
Participant 5	39	133	8.62(1.76)	.06(.14)	9.043***	.000	-7.392***
Participant 6	37	129	8.63(1.76)	.06(.14)	9.733***	.006	-7.525***
Participant 7	40	133	8.35(2.03)	.22(.25)	9.326***	-.009	-1.956
Participant 8	42	133	9.39(.80)	.17(.21)	9.355***	-.003	1.241
Participant 9	33	133	8.70(1.52)	.31(.24)	8.437***	.013	-1.483
Participant 10	38	133	9.31(1.37)	.10(.14)	9.915***	.001	-6.472***

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Table 3
Unstandardized Coefficient of DCCS Accuracy and Chi-Square Change of Constrained Models

	Participant 5	Participant 3	$\Delta\chi^2$ when constrained to be equal
Intercept	9.043***	6.356***	16.952(1) ***
Lag	.000	.035***	15.700(1) ***
Off-task	-7.392***	-3.105	2.755(1)
	Participant 5	Participant 2	$\Delta\chi^2$ when constrained to be equal
Intercept	9.043***	7.420***	3.086(1)
Lag	.000	.010	0.844(1)
Off-task	-7.392***	-0.845	6.891(1) **
	Participant 5	Participant 6	$\Delta\chi^2$ when constrained to be equal
Intercept	9.043***	9.733***	0.967(1)
Lag	.000	.006	0.364(1)
Off-task	-7.392***	-7.525***	0.003(1)

Note. * $p < .05$, ** $p < .01$, *** $p < .001$.

Last, utilizing the MCMC-imputed individual daily latent scores, we calculated the covariation between off-task and accuracy for each individual, respectively, as well as for the daily across-individual means. Significant correlations between off-task and accuracy scores suggest intraindividual variability can be meaningfully explained by variability in attention level.

Results

Descriptive results and regression coefficient are shown in Table 2. According to the individual linear regressions, all participants except Participant 3 showed no significant linear change in accuracy during the period of participation. Participant 3 had the lowest starting point of accuracy but showed a significant improvement in accuracy. Three of the 10 participants (Participants 5, 6, and 10) demonstrated a negative association between off-task mean and Accuracy. The descriptive and regression results preliminarily suggest that individuals showed meaningful differences in fluctuation and directional change from other individuals.

Multi-Group Analysis Among Three Pairs of Participants

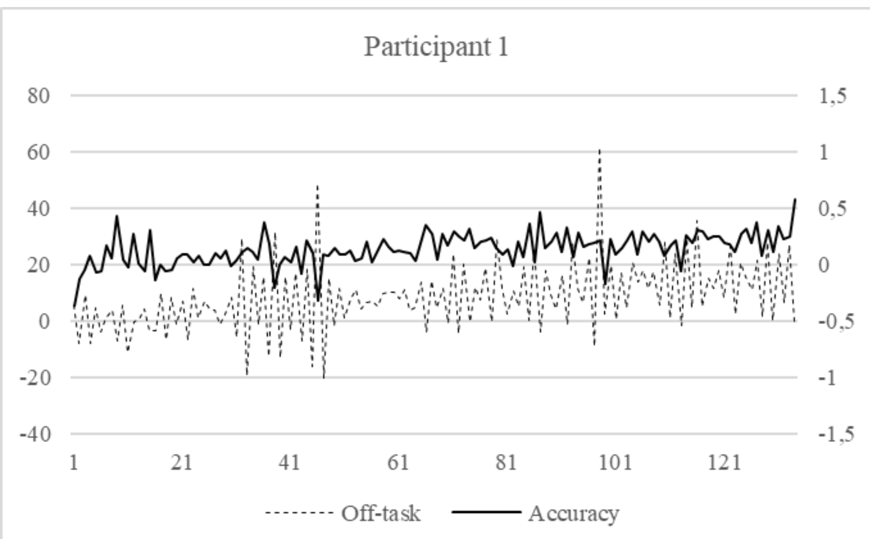
To further answer the first research question of whether individuals can have meaningful differences in changes in EF, multi-group analyses were conducted among three pairs of participants (see Table 3): Participants 5 and 3, Participants 5 and 2, and Participants 5 and 6. Each pair of participants demonstrated a different pattern of meaningful individual differences. According to the multi-group analyses, Participants 5 and 3 demonstrated significant differences in intercept and Lag coefficient. Participant 5 had a higher starting point than Participant 3, but Participant 3 showed significant growth in accuracy, whereas Participant 5 did not show such growth. In contrast to the first pair, comparisons between Participants 5 and 2 indicated that the significant difference lay in the off-task coefficient. Although Participants 5 and 2 showed similar starting points and lack of growth in accuracy, the off-task score was negatively linked to accuracy for Participant 5 but not for Participant 2. The comparison between Participants 5 and 6 was an example of similar individuals who had similar starting points, growths, and connections to off-task performance. The findings suggest that some individuals are like others, whereas some individuals are different from other individuals in different aspects of EF development. As explained by Molenaar and Nesselroade (2015), some but not all individuals have person-specific trajectories that may be aggregated.

Dynamic Structural Equation Modeling (DSEM) for Individuals and Group

The results from the DSEM models addressed the second and third research questions. Using MCMC-imputed factor scores for every possible time point (i.e., daily), time-series plots of off-task and latent accuracy scores are shown in Figure 2. Each individual demonstrated distinctive patterns of fluctuation, directional change, and correlation of the two latent factors, which were visually different from the group-based plots. The group time-series plots were created based on the average score across 10 participants for each measurement occasion, demonstrating much smoother trajectories than any individual in the group. Overall, the between-level result demonstrated non-significant intraindividual variance, slope, and autoregression for both off-task and accuracy latent factors. However, such results were not representative of any participant in this group. Although none of the participants showed significant AR(1) for off-task or accuracy, most participants showed significant variance in the accuracy latent scores, and fewer showed significant variance in the off-task latent scores. Moreover, participants also showed different slopes in off-task and accuracy. Participant 2 showed a significant decrease in off-task, whereas Participants 8, 9, and 10 demonstrated upward trends in off-task. Participants 3 and 9 demonstrated growth in accuracy. However, no other participant demonstrated a clear trend in accuracy.

Participants 1 and 3 showed non-significant correlations between off-task and accuracy. Among the rest of the eight participants, Participants 8 and 9 showed a positive correlation between off-task and accuracy, but the rest of the correlations were negative. Interestingly, although the majority of the participants demonstrated a negative association between off-task and accuracy scores, the group-based results demonstrated a positive association between off-task and latent accuracy scores. In sum, all participants displayed uniqueness in the fluctuation of EF performances, and some participants showed the meaningfulness in their intraindividual variability via the association between accuracy and off-task scores.

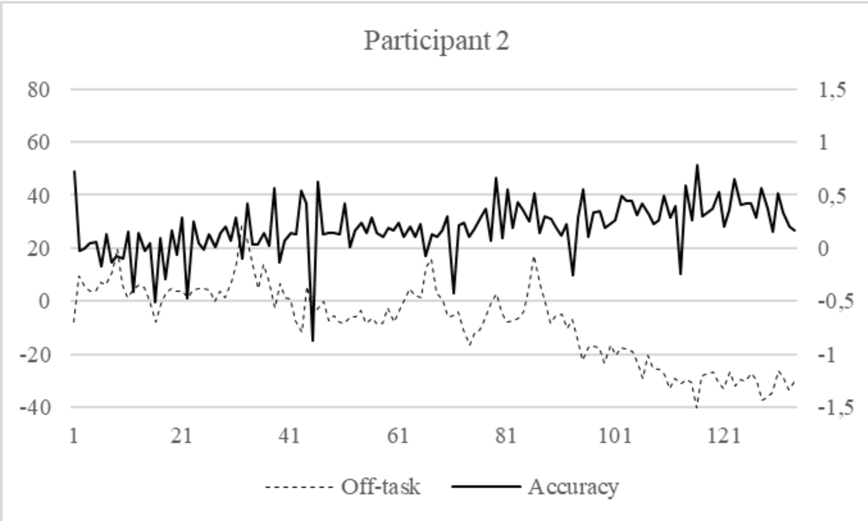
Figure 2.
Time-series of off-task and accuracy for 10 participants and the whole group. The left y-axis is for off-task latent scores, and the right y-axis is for accuracy scores. Confidence intervals were presented. Significant parameters were bolded.



$LogV_{off\text{-}task}$= 1.68 [.52, 2.61]
$Slope_{off\text{-}task}$= .18 [-.44, .71]
$AR(1)_{off\text{-}task}$= -.56 [-.88, .10]

$LogV_{accuracy}$= 2.67 [1.12, 2.08]
$Slope_{accuracy}$= .00 [-.01, .01]
$AR(1)_{accuracy}$= -.05 [-.58, .47]

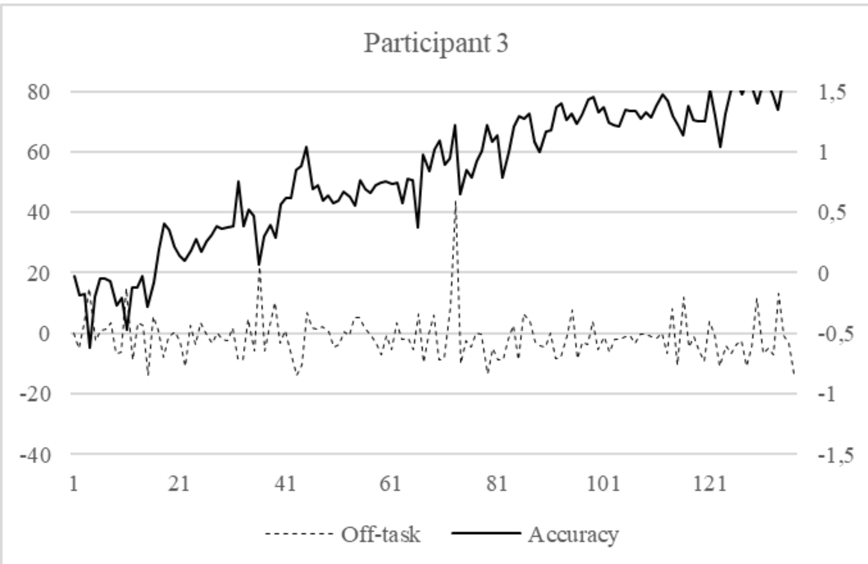
Correlation = .10 [-.07, .27]



LogV$_{\text{off-task}}$= 1.05 [-.47, 2.01]
Slope $_{\text{off-task}}$= -.07 [-.34, .00]
AR(1)$_{\text{off-task}}$= .47 [-.20, .98]

LogV$_{\text{accuracy}}$= 3.05 [1.97, 4.24]
Slope $_{\text{accuracy}}$= .00 [-.01, .02]
AR(1)$_{\text{accuracy}}$= -.23 [-.71, .45]

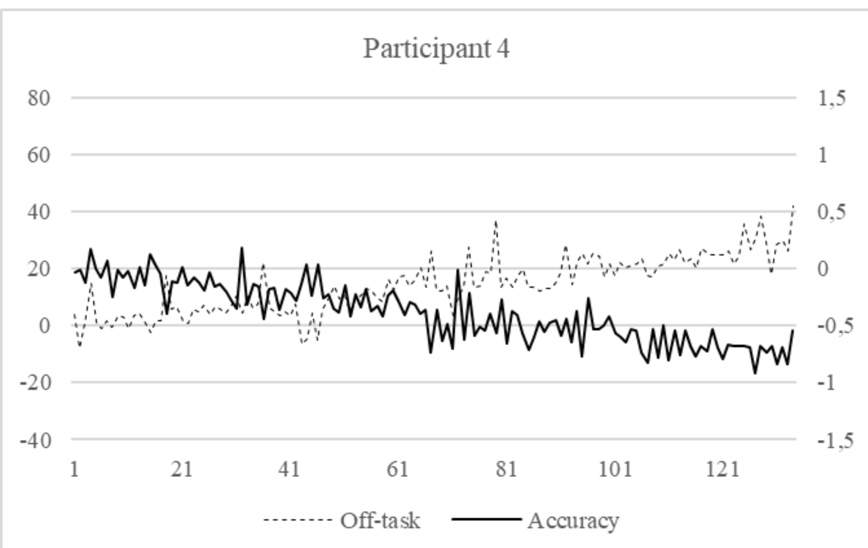
Correlation = -.43 [-.60, -.23]



LogV$_{\text{off-task}}$= 1.40 [.12, 2.62]
Slope $_{\text{off-task}}$= -.01 [-.21, .17]
AR(1)$_{\text{off-task}}$= -.09 [-.59, .40]

LogV$_{\text{accuracy}}$= 2.83 [1.61, 3.58]
Slope $_{\text{accuracy}}$= .01 [.00, .03]
AR(1)$_{\text{accuracy}}$= .30 [-.61, .91]

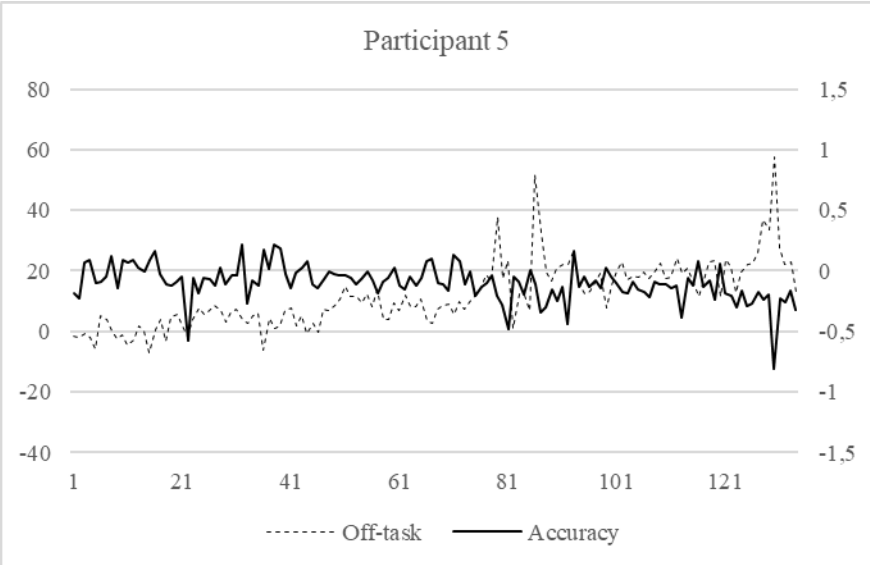
Correlation = -.15 [-.31, .02]



LogV$_{\text{off-task}}$= 1.03 [-.52, 1.92]
Slope $_{\text{off-task}}$= .20 [-.01, .61]
AR(1)$_{\text{off-task}}$= -.01 [-.67, .61]

LogV$_{\text{accuracy}}$= 2.82 [.94, 4.00]
Slope $_{\text{accuracy}}$= -.01 [-.03, .00]
AR(1)$_{\text{accuracy}}$= -.13 [-.88, .62]

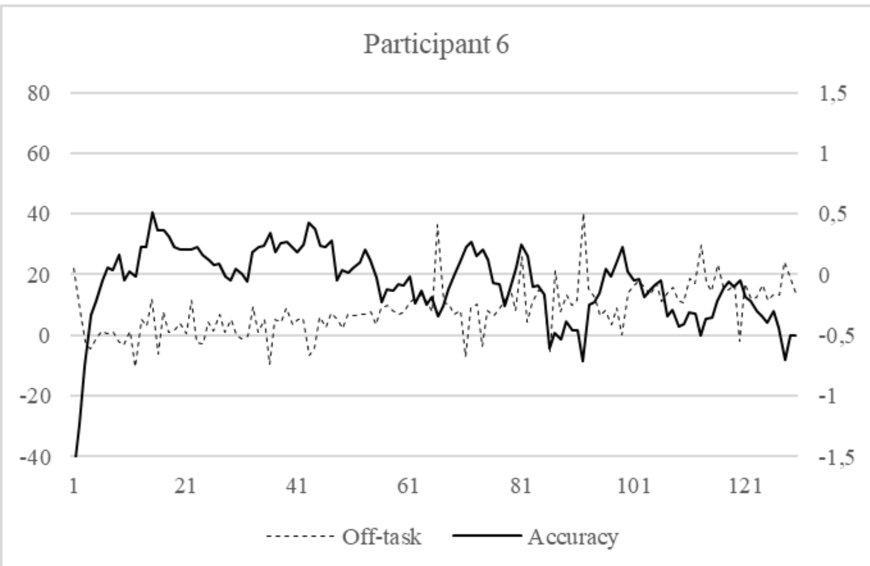
Correlation = -.78 [-.84, -.70]



LogV$_{\text{off-task}}$= 1.48 [.55, 2.24]
Slope $_{\text{off-task}}$= .15 [-.09, .59]
AR(1)$_{\text{off-task}}$= .10 [-.51, .67]

LogV$_{\text{accuracy}}$= 2.47 [1.46, 3.85]
Slope $_{\text{accuracy}}$= -.00 [-.01, .00]
AR(1)$_{\text{accuracy}}$= .09 [-.59, .68]

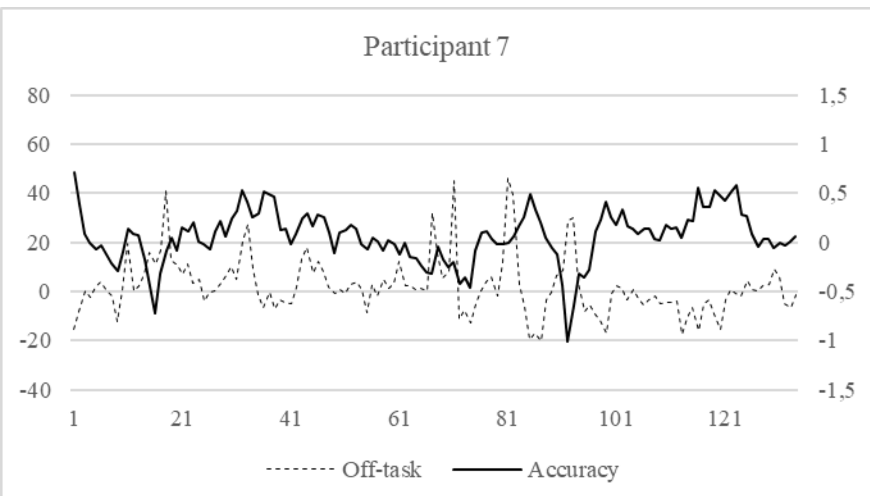
Correlation = -.56 [-.66, -.43]



LogV$_{\text{off-task}}$= 1.08 [-.37, 2.30]
Slope $_{\text{off-task}}$= .12 [-.02, .37]
AR(1)$_{\text{off-task}}$= .04 [-.65, .54]

LogV$_{\text{accuracy}}$= 3.30 [1.73, 4.33]
Slope $_{\text{accuracy}}$= -.00 [-.01, .00]
AR(1)$_{\text{accuracy}}$= .63 [-.22, .86]

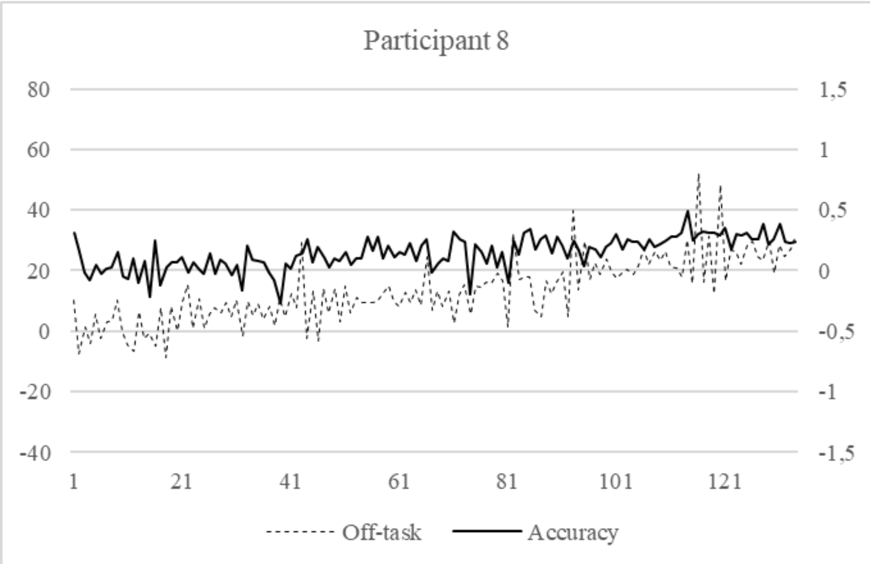
Correlation = -.49 [-.61, -.35]



LogV$_{\text{off-task}}$= 1.73 [.66, 2.51]
Slope $_{\text{off-task}}$= .01 [-.16, .14]
AR(1)$_{\text{off-task}}$= .31 [-.41, .78]

LogV$_{\text{accuracy}}$= 2.84 [1.43, 4.02]
Slope $_{\text{accuracy}}$= .00 [-.00, .00]
AR(1)$_{\text{accuracy}}$= .54 [-.15, .86]

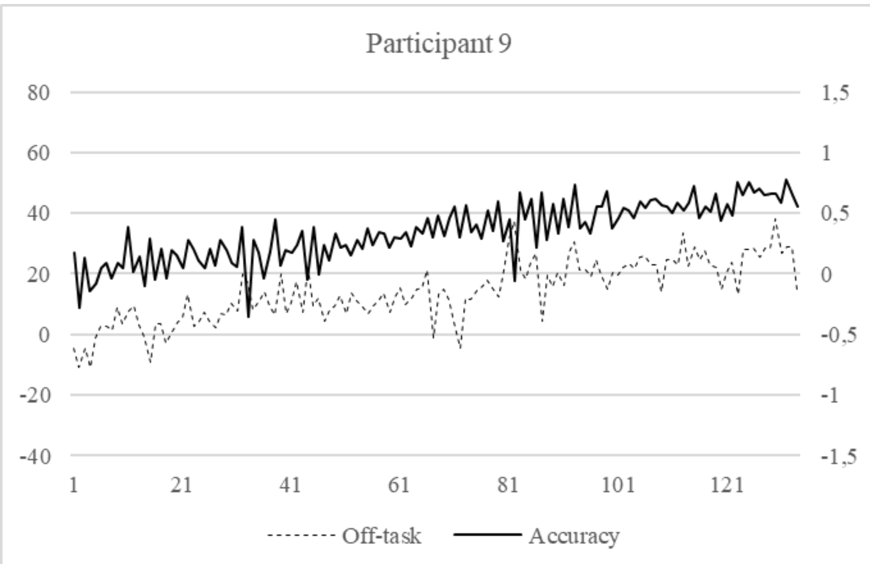
Correlation = -.32 [-.46, -.16]



$LogV_{off\text{-}task}$= .99 [-.45, 1.85]
$Slope_{off\text{-}task}$= .24 [.01, .52]
$AR(1)_{off\text{-}task}$= -.17 [-.86, .53]

$LogV_{accuracy}$= 2.68 [.81, 3.78]
$Slope_{accuracy}$= .00 [-.01, .02]
$AR(1)_{accuracy}$= -.06 [-.75, .53]

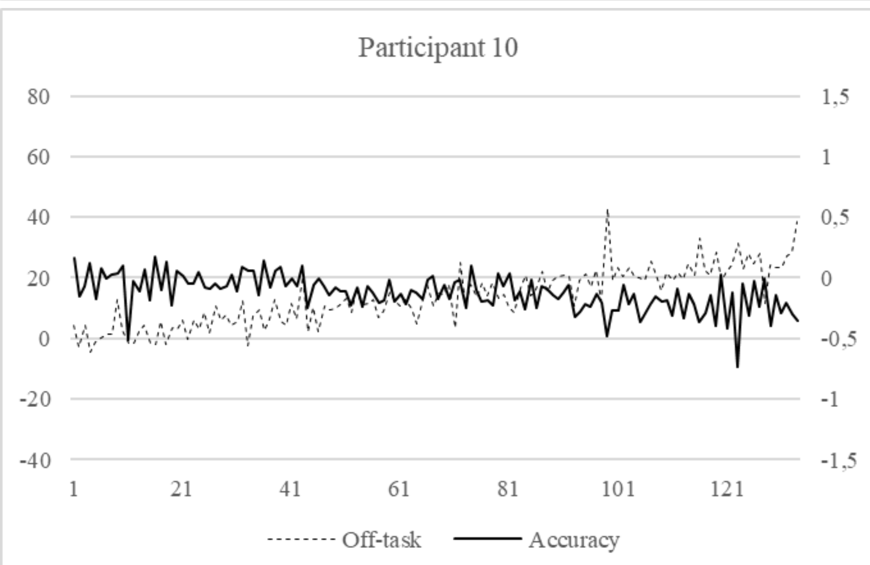
Correlation = .57 [.44, .67]



$LogV_{off\text{-}task}$= 1.21 [-.41, 2.05]
$Slope_{off\text{-}task}$= .16 [.05, .50]
$AR(1)_{off\text{-}task}$= .11 [-.52, .66]

$LogV_{accuracy}$= 2.84 [1.60, 4.07]
$Slope_{accuracy}$= .01 [.00, .03]
$AR(1)_{accuracy}$= -.24 [-.78, .23]

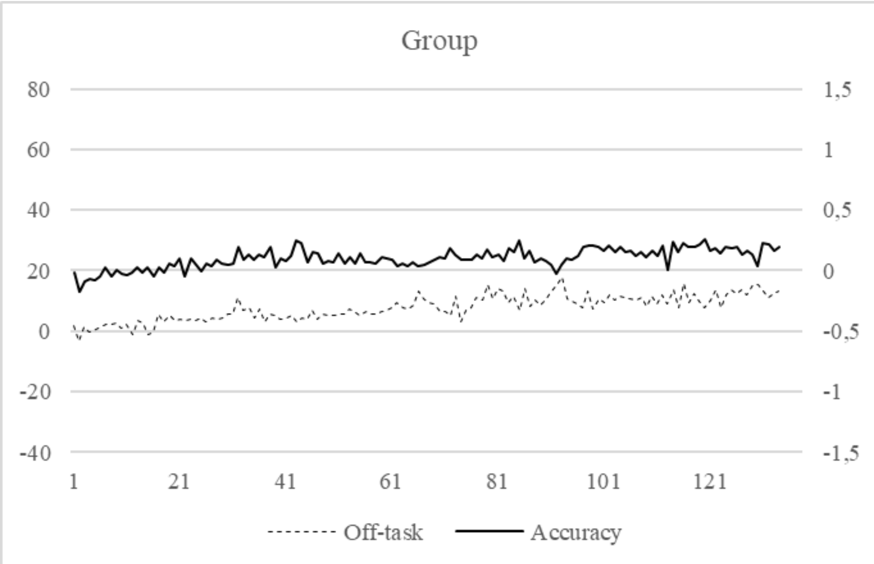
Correlation = .63 [.51, .72]



$LogV_{off\text{-}task}$= .64 [-1.18, 3.23]
$Slope_{off\text{-}task}$= .03 [-.20, .29]
$AR(1)_{off\text{-}task}$= .07 [-.34, .52]

$LogV_{accuracy}$= 2.04 [-.07, 4.18]
$Slope_{accuracy}$= .01 [-.21, .24]
$AR(1)_{accuracy}$= .05 [-.40, .50]

Correlation = .58 [.45, .68]



$LogV_{off\text{-}task}$= .64 [-1.18, 3.23]
$Slope_{off\text{-}task}$= .03 [-.20, .29]
$AR(1)_{off\text{-}task}$= .07 [-.34, .52]

$LogV_{accuracy}$= 2.04 [-.07, 4.18]
$Slope_{accuracy}$= .01 [-.21, .24]
$AR(1)_{accuracy}$= .05 [-.40, .50]

Correlation = .58 [.45, .68]

Discussion

What may be termed the traditional "aggregate-then-analyze" approach (Mascolo & Fischer, 2015; Molenaar & Nesselroade, 2015; Rose, 2016) may mask meaningful individuality. In order to understand person-specific EF changes and fluctuation among children, this exploratory study used an idiographic data-analytic approach within an intensive longitudinal design. This study explored whether an idiographic approach could contribute to understanding EF development differently than the traditional variable-centered approach. The results demonstrated that individuals showed meaningful differences in fluctuation and directional change in EFs. Moreover, the group trajectory was not representative of the individual trajectories. Intraindividual variability in EFs was also meaningful, as it could be partially explained by another cognitive factor - attention level, which fluctuated on a daily basis.

Using Participant 5 as the reference individual, the multi-group analyses demonstrated that individuals could differ from other individuals in different aspects of development. Compared to Participant 3, Participant 5 showed a higher starting point in EF but no growth over time. However, compared to Participant 2, the difference centered around the impact of daily attention level indexed by off-task mean. Participants 5 and 6 exhibited similarities across constructs of interest. Although the findings of the three pairs were limited by "cherry picking" selection bias, and such findings are not generalizable to any other group in the development of EF, they supported the existence of person-specific development. Consistent with the Kluckhohn and Murry (1953) statement that every individual can be like all other people, like only some other people, or like no other person in regard to specific domains of development, the three selected pairs of participants served as examples to demonstrate three different scenarios: when participants differed in level and change in EF but not in relations between EF and inattention, when participants differed in relations between EF and inattention but not in level and change in EF, and when participants did not differ in level, change, and relations between constructs of interest. Such findings reflect the Specificity Principle (Bornstein, 2017) and support the idea that development is specific to an individual at a specific time and place (in the case of this study, place of testing).

Although all the participants completed the online DCCS task in the same classroom at almost the same time, other aspects of their lives likely varied, which—although not assessed in the present study—might be related to interindividual variation in intraindividually specific EF performance and trajectories. When using a variable-centered approach, it is assumed that there is a universal process of development of EF across individuals, and that "true mechanisms" can be revealed by creating the average of a large group of people (Speelman & McGann, 2013). However, the multi-group results suggest that such an assumption may not be valid. Indeed, we believe our findings, albeit preliminary, support the idea that individuality is not simply "error" but valuable information that can be statistically assessed. Future developmental studies should evaluate the reality of "universal" processes in development before aggregating individual data (Mascolo & Fischer, 2015; Molenaar & Nesselroade, 2015).

Although constraining parameters pair by pair can determine whether aggregation is possible for a specific pair of youth, it is not practical to make such comparison for each possible pair (N = 45) until the entire sample of 10 participants is assessed. Using DSEM enabled us to estimate both individual-specific results as well as the group-level trajectory and fluctuation. The time-series plots further demonstrated the uniqueness of individual-specific trajectories. Using the group-based trajectory, developmental scientists may fail to recognize the significant intraindividual variability in EF performance on a daily basis and assume that no directional change has happened during the four months of data collection. However, such an inference would not represent any specific participant we sampled. All participants showed unique patterns of fluctuation that cannot be represented by the trajectory of group-based means. The DSEM results further supported the Specificity Principle (Bornstein, 2017), suggesting that universality is sparse but uniqueness universal. Again, future studies should be cautious when making inferences about individuals based solely on group-based means.

Using the imputed latent scores of off-task and accuracy generated by the DSEM model, the bivariate correlation between off-task and accuracy was created for each child. Six out of the 10 participants demonstrated a negative correlation, suggesting that a lower attention level was associated with worse daily EF performance. However, for Participants 8 and 9, lower attention level was associated with better daily EF performance. The significant correlations between off-task and accuracy suggest that daily attention level could be an important cognitive factor that contributes to intraindividual variability in EFs, and the specific role of this factor can be different for different individuals. However, none of the participants demonstrated a significant AR(1), suggesting that the previous score was not predictive of the current score. We only had 10 participants in the current study, and it is possible that the autoregressive effect is unique to some people, but our ten participants happened to have no autoregressive effect; neither in attention nor EFs. Another plausible explanation is that EFs may show rhythmic patterns at a timescale smaller than a day. Future studies could include intensive data collection of EF within a day to examine the within-day fluctuation of EFs.

Limitations and Future Research

This study was the first to use an idiographic approach in the study of EFs among youth in late childhood/early adolescence. Previous studies of EF development among school-aged children have mainly utilized a variable-centered approach, either comparing school-aged children of different age groups or collecting data at multiple widely spaced timepoints among the same group of children (e.g., Huizinga et al., 2006; Finch et al., 2019). These studies provided evidence that EF is still improving during middle to late childhood or even later. However, conclusions were based on group-based means and interindividual variance. The current study demonstrated the uniqueness of individual trajectories of EFs within a few months, suggesting that the conclusions of the group-based average may not be applicable to specific individuals. We should keep in mind that EFs were only measured via the short DCCS, which weighs heavily on the cognitive flexibility component. Future studies should use multiple comprehensive measurements to include inhibitory control and working memory to examine the latent structure of EFs intensively.

Second, the intraindividual fluctuation within a short period of time provided new perspectives in understanding EF development. The nature of EF development may not only lay in the change of mean scores in EF tasks but in the changes of EF fluctuations. However, the current time-series models are considered stationary models, which assumes that the pattern of fluctuation (i.e., LogV, AR(1), slope) was stable across time (Hamilton, 1994; Haslbeck et al., 2020). Although we accounted for a systematic trend in the data (i.e., though detrending), we cannot know whether the AR(1) and LogV stayed the same across the entire data collection period. Future studies should include a longer period of time with more regular data collections to model time-relevant fluctuations as an innovative way to show EF development in the aspect of fluctuations. It is also worth pointing out that the interpretation of the slope in EF performance is challenging because this slope could be due to developmental change or to practice effects during the intensive repeated measures (Erkkila et al., 2018; Schmiedek et al., 2010).

Because the current study aimed to show unique person-specific trajectories instead of generalizable results, we only included 10 participants. With such a small sample, it was difficult to model more unique patterns of fluctuation. The inclusion of the 10 participants can also be a result of selection bias because only participants who were willing to complete tasks consistently can provide sufficient data for idiographic analyses. Moreover, using only one EF task made it impossible to examine the unique latent structure of EFs and to search for similarities in the EF latent structures across individuals. The present research constitutes only a first step in applying idiographic approaches to understanding EF and other aspects of development among young people. With promising findings in the uniqueness of individual fluctuation, future studies may be aimed at assessing whether there are unique associations between EF fluctuation and context; if so, such research will contribute to advancing the understanding of how EF may develop across micro and macro timescales.

Author contributions

DY drafted the first version of the manuscript, carried out the statistical analyses, and was actively involved in revising the manuscript. PJY carried out the statistical analyses and was actively involved in drafting the first version of the manuscript and in revising the manuscript. GJG was actively involved in drafting the first version of the manuscript and in revising the manuscript. CPT was actively involved in drafting the first version of the manuscript. PKG designed the data collection platform and was actively involved in drafting the first version of the manuscript. PAC was actively involved in study design and data collection and edited the first draft. RML served as the PI of the study, designed the study, and was actively involved in drafting the first version of the manuscript and in revising the manuscript.

Declaration of interests

All authors declare that there is no conflict of interest.

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Action editor

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