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Abstract

The predictive validity of performance on cognitive-behavioral measures of executive function (EF) suggests that these measures index children's underlying capacity for self-regulation. In this paper, we apply ecological systems theory to critically evaluate this assertion. We argue that as typically administered, standard measures of EF do not index children's underlying, trait-like capacity for EF, but rather assess their state-like EF performance at a given point in time and in a particular (and often quite peculiar) context. This underscores the importance of disentangling intra-individual (i.e., state-like) and inter-individual (trait-like) differences in performance on these measures and understanding how factors at various levels of organization may contribute to both. To this end, we offer an approach that combines the collection of repeated measures of EF with a multilevel modeling framework, and conclude by discussing the application of this approach to the study of educational interventions designed to foster children's EF.

Keywords: executive function; self-regulation; ecological systems theory; individual differences; multilevel modeling

An Ecological Systems Perspective on Individual Differences in Children's Performance on Measures of Executive Function

The past three decades have seen a tremendous growth of interest in the development of children's executive function (EF), partially driven by the predictive validity of cognitive-behavioral measures of EF with respect to key educational outcomes. Results of this sort offer confidence that when we administer these measures, we are assessing children's underlying capacity for EF. In this paper, we critically evaluate this assertion through the lens of ecological systems theory (Bronfenbrenner, 1979; Bronfenbrenner & Morris, 2006), arguing that children's performance on any measure of EF indexes their *state*-like EF at a given point in time and in a particular context. State-like EF may reflect but is not synonymous with children's *trait*-like EF: their underlying capacity to exercise EF across time and contexts. This distinction underscores the need to disentangle state- and trait-like contributions to individual differences in children's performance on measures of EF, and to account for factors that may contribute to intra-individual variability in state-like performance. In this paper we use a systems theory framework to enumerate these factors at different levels of the developmental environment, and outline one approach for disentangling state- and trait-like contributions to individual differences in performance. We conclude by discussing the implications of this perspective for future research, with a particular emphasis on the evaluation of educational interventions designed to foster children's EF.

The Measurement of Executive Function and its Interpretation

The term EF refers to a set of core cognitive processes that often include working memory, inhibitory control, and cognitive flexibility (Willoughby et al., 2014), although there is ongoing debate about precisely which processes should be included in or excluded from EF (see, for example, meta-analytic results by Karr et al. (2018) and Miyake & Friedman, 2012). Nevertheless, there is emerging consensus that these processes comprise an essential component of self-regulatory function, though they do not encompass all aspects of that function (Holochwost, Kolacz, & Mills-Koonce, 2021). Accordingly, there has been a tremendous degree of interest in understanding EF and its development across childhood and adolescence, in part because of reasonably-consistent associations between age and children's performance on measures of EF (e.g., Doebel & Zelazo, 2015) and the implications of these associations for understanding children's self-regulatory development and the underlying function of the prefrontal cortex (Diamond, 2013; Grodzinsky & Diamond, 1992; Taylor et al., 2004), and in part because of the robust correlations between children's performance on measures of EF and a variety of educational outcomes, including school readiness (McClelland & Cameron, 2012), academic achievement throughout early elementary school (Davies et al., 2016; Spiegel et al., 2021), and higher likelihoods of graduating from high school (Hernandez, 2011) and matriculating to college (Lesnick et al., 2010).

The predictive validity of performance on measures of EF is even more remarkable when one considers how these measures are typically administered. Working in a one-on-one setting, a researcher will guide the child through measures with the aid of a computer (e.g., EF Touch; Willoughby et al., 2010) or by using a standard protocol (e.g., the Peg-Tapping task; Diamond & Taylor, 1996), with each measure lasting for a few minutes. Children's performance on these measures is then typically interpreted as the child's underlying capacity to exercise EF within the domain(s) that the task is understood to measure. This interpretation is often implied by the language used to describe performance on a measure (or measures) of EF (e.g., "levels of [maternal] sensitivity predicted **lower levels of executive functions**" (emphasis added);

Holochwost et al., 2016, p. 543). The predictive validity of these measures invites this interpretation – what better evidence could there be that performance on these measures captures children's underlying capacity for EF than the fact that they predict school readiness (for example) more strongly than IQ predicts school readiness (Blair & Razza, 2007)?

Applying an ecological systems perspective to children's performance on cognitive-behavioral measures of EF prompts us to reconsider this interpretation. As Doebel (2020) notes, although the origin of many of these measures as neuropsychological tests and the construction of composite (e.g., Carlson & Moses, 2001) or latent indices of performance (Miyake et al., 2000) suggests that it is possible to achieve a "pure" index of children's EF, children's performance on a given measure of EF cannot, in fact, be separated from the demands of the task. Moreover – and to paraphrase Bronfenbrenner (1979) – children's performance on any measure of EF features a contrived task that is divorced from the contexts in which children typically practice EF (e.g., the home, the classroom), administered by a person with whom the child is generally unfamiliar (a researcher) over a brief period of time.

Considering time (the chronosystem, per ecological systems theory) when interpreting children's performance on these measures suggests that what we are in fact assessing is a child's phenomenological, state-like capacity to exercise their EF at a given point in time and in a particular context, not trait-like EF capacity in any neumonological sense (that is, as EF capacity *is*, rather than as it is *observed*). This may explain the fact that children's performance on cognitive-behavioral measures of EF display modest to moderate levels of test-retest reliability (Beck et al., 2011; Mueller & Kerns, 2015; Willoughby et al., 2017). It may also partially account for the low correlations between performance on these measures and parents' ratings of EF (Mueller & Kerns, 2015; Toplak, West, & Stanovich, 2013; Silver et al., 2014), given that these questionnaires typically reference broader periods of time and a wider range of contexts (Isquith et al., 2013), and, therefore, exhibit high levels of test-retest reliability (Catale et al., 2015; Enkvani et al., 2019; Gioia et al., 2002; Thorell & Nyburg, 2008). In short, state-like EF *should* reflect trait-like EF, but the extent to which it does is unknown and may vary both between individuals and within individuals over time. Understanding the extent to which we are measuring children's underlying EF capacity when administering cognitive-behavioral measures of EF requires that we disentangle state- and trait-like contributions to individual differences in performance on these measures, and then carefully consider the factors that may influence state-like performance.

Applying an Ecological Systems Perspective to Understanding Intra-individual Differences in State-Like Executive Function

Fortunately, ecological systems theory provides a framework to understand these factors and their collective influence on state-like performance. Here we identify a small number of factors that prior research suggests may impinge upon state-like EF performance located at three levels of proximity to the child: intra-individual factors, factors located within the immediate context of the testing environment, and factors located within the broader microsystem of the home. The enumeration of these particular factors is not intended as a comprehensive accounting of the factors that might impact state-like EF, but rather as an initial set of illustrative examples.

Intra-individual factors. Reaction time is one intra-individual factor that contributes to *inter*-individual differences in performance on cognitive-behavioral measures of EF (Blair et al., 2005); some children are simply able to respond more quickly than others to the requests for responses imposed by measures of EF. Indeed, one recent study reported that inter-individual differences in intra-individual variability of reaction time on an EF task was a stronger predictor of individual differences in academic outcomes than differences in task accuracy (Cubillo et al., 2022).

For measures that use reaction time to index performance (e.g., the go/no-go task; Torpey et al., 2012), understanding sources of intra-individual variability in reaction time is essential to understanding intra-individual differences in state-like performance. One source of intra-individual variability in reaction time is a child's willingness to persist in the EF measure, which would reflect that child's more general, trait-like characteristic of persistence. Task persistence may itself fluctuate across multiple administrations of the measure as a function of factors at other levels of the environment (see below). However, *inter*-individual differences in children's trait-like persistence can also contribute to state-like, intra-individual differences in reaction time within a single administration of a measure.

Consider the case of a go/no-go task that lasts for 80 trials. A child who exhibits high levels of trait-like persistence will also exhibit relatively consistent reaction times to each successive trial of the task. Therefore, the child's performance on the first 20 trials (as indexed by the difference in their reaction time to correct trials and their reaction time to all trials; Torpey et al., 2012) will be an equally-valid index of their underlying, trait-like inhibitory control as their performance on the final 20 trials. However, for a child who exhibits lower levels of trait-like persistence, reaction time may become more variable as the measure continues and their task engagement declines. For this child, performance on the first 20 trials is a more valid index of their underlying, trait-like *capacity* for inhibitory control than their performance on the last 20 trials.

Intra-individual variability in a child's performance on EF measures will reflect many inter-individual factors in addition to persistence. One set of factors is the activity of the neurophysiological systems that mobilize metabolic resources in response to situational demands, including the demands imposed by measures of EF. As in the case of reaction time, there is a compelling body of research that has examined the contribution of these systems to *inter*-individual differences in performance on measures of EF (cf., Blair & Raver, 2015). However, very little is known about how the activity of these systems may contribute to *intra*-individual variability in performance on these measures, though prior research suggests that such a contribution would be observed across multiple time scales, each corresponding to the normative time scale of activity within a given neurophysiological system.

Baseline levels of HPA-axis activity, for example, follow a predictable circadian or diurnal rhythm in all but the youngest children (de Weerth, Zijl, & Buitelaar, 2003) and baseline levels of HPA-axis activity have also been linked to performance on measures of EF (Obradović et al., 2016). Therefore, diurnal fluctuations in baseline HPA-axis activity may contribute to intra-individual differences in performance on measures of EF administered at different times of day across multiple days (and indeed, studies of older adults have found an effect of time of day on cognitive performance; see Overton et al., 2016). However, more temporally-dynamic neurophysiological systems that modulate metabolic output on a moment-to-moment basis have the potential to contribute to intra-individual differences in performance within a single measure of EF. These include the parasympathetic (PNS) and sympathetic nervous systems (SNS), which (among many other things) modulate levels of catecholamines in the putative seat of EF, the prefrontal cortex. Although individual differences in the phasic activity of the PNS (Marcovitch et al., 2010) and the SNS (Arnsten, 2015) across the entirety of an EF measure have been linked to individual differences in performance on that measure, to date patterns of covariation between moment-to-moment fluctuations in these systems and trial-to-trial fluctuations in performance on measures of EF has not been examined.

The microsystem of the testing context. At the most fundamental level, the microsystem of the testing context comprises the EF measure itself: it is the key object or symbol set in the physical environment with which the child interacts (Bronfenbrenner & Morris, 2006). Therefore, it is important to understand how measure characteristics may contribute to intra-individual variability in performance, either independently or via their interaction with factors at other levels of organization. For example, the length of a measure may interact with children's task persistence to contribute to intra-individual variability in performance.

Another characteristic of EF measures that may contribute to intra-individual variability in performance is whether they are "cool," decontextualized tasks or "hot" tasks that elicit an emotional investment that may influence children's motivation (Zelazo & Carlson, 2012). What ultimately matters is the child's *perception* of measure as cool or hot, which is very likely to vary from one child to the next, but which may also vary from one point in time to another according to other factors in the microsystem of the testing context. One of these factors is the rapport between child and researcher. When asked to complete a measure, a child – and particularly a younger child – may interpret this as a personal request by the researcher. The child's emotional investment in the measure and their motivation to comply with the researcher's request will therefore be based, in part, on their rapport with that researcher and the extent to which they perceive that the researcher in invested in their performance (Doebel, 2020).

A more positive child-researcher rapport has been found to improve children's performance on measures of EF (Gidron et al., 2020). While a number of factors may influence child-researcher rapport, one may be the demographic match (or mismatch) between child and researcher. The effect of this match on children's performance on cognitive assessments is well-established (Samuel, 1977), and is driven by a combination of stereotype threat on the part of the child and implicit bias on the part of the researcher (Joshi, Doan, & Springer, 2018). Therefore, changes in child-researcher match that accompany changes in who is administering an EF measure from one point in time to another may be an important source of intra-individual variability in children's performance.

The broader microsystem. Beyond the immediate context of the testing environment lie the microsystems of the child's developmental ecology, including the home environment. Although there is a robust literature linking the quality of the home environment to inter-individual differences in what is implicitly assumed to be children's trait-like EF (see Lawson et al., 2018, but also Miller-Cotto et al., 2022, for further considerations), far less attention has been paid to understanding how fluctuations in factors located in this microsystem may contribute to intra-individual variability in children's state-like performance on measures of EF. This is problematic, given what is known about how apparently-minor fluctuations in factors linked to the home environment can influence children's performance on cognitive assessments.

Consider the impact of the home environment on children's nutrition. As noted above, meeting the situational demands imposed by completing measures of EF requires the mobilization of metabolic resources, including the brain's principal fuel, glucose. Fluctuations in children's blood glucose levels have been linked to performance on a variety of cognitive assessments (Jirout et al., 2019). A child who is consistently well-nourished, will, by definition, experience few fluctuations in their blood glucose levels from a given point in time on one day to the same point in time on another day. All else being equal, we would expect this child to exhibit a lower degree of intra-individual variability in their state-like performance on measures of EF administered at the same time of day on multiple days. The same would be true for a child who is consistently under-nourished, whose blood glucose levels would be consistently low at a given time from one day to another. In both cases, the lower degree of intra-individual variability would result in an increased correspondence between observed state-like performance and underlying trait-like EF.

Things become more complex when we consider the case of a child who is inconsistently nourished – a child whose family is, for example, experiencing food insecurity. For this child, blood glucose levels at a given point in time may vary widely from day to day as a function of when they last ate: for example, levels of blood glucose at ten in the morning would be higher on a day the child had breakfast than on a day when they did not. Their state-like EF performance may covary with their nutritional intake, with better performance observed on days when the child is relatively well-nourished, and worse performance on days when they are not. For this child, we would expect to observe greater intra-individual variability in their performance, and, therefore, reduced correspondence between their state- and trait-like EF.

Another aspect of the home environment that may contribute to intra-individual variability in children's performance on measures of EF is the duration and quality of their sleep. School-age children require roughly 10 hours of sleep across the day, with younger children requiring longer and more frequent sleep opportunities to support optimal development (Schotland & Sockrider, 2017). Insufficient sleep quantity and quality is associated with poorer performance on cognitive assessments in childhood, including measures of EF (Gruber, et al., 2012).

Just like a child who is consistently well-nourished, a child who consistently gets sufficient or insufficient sleep is likely to exhibit less intra-individual variability in their performance on measures on EF. In either case, a lower degree of intra-individual variability increases the correspondence between state-like performance and trait-like EF capacity for these children. However, a child who gets sufficient sleep one night and insufficient sleep the next is more likely to exhibit a higher level of intra-individual variability in their state-like performance, and, as such, state-like performance at a given point in time may be a poorer indicator of trait-like EF capacity. The examples of nutrition and sleep illustrate the particular salience of environmental chaos when considering intra-individual variability in children's state-like performance on measures of EF, which is one of a number of a super-ordinate environmental factors with the potential to disrupt or disorganize interactions between the child and multiple aspects of the microsystem (Evans & Wachs, 2010), including food security (Evans et al., 2005) and sleep (Boles et al., 2017; see Munakata & Michaelson for other such super-ordinate factors contained within the broader social-developmental context).

Summary. In this section, we have reviewed a number of factors that may contribute to intra-individual variability in state-like performance on measures of EF. In doing so, we have also highlighted how these factors may interact to make contributions to intra-individual variability, a possibility that is consistent with a dynamic systems perspective on EF recently proposed by Perone and colleagues (2021). Our focus on the particular interactions mentioned above is not meant to imply that these are the only interactions of interest for future research; rather, as Perone et al. (2021) note, a dynamic systems perspective would suggest the interactive contributors to intra-individual variability in performance on measures of EF are located at many levels of the developmental environment. Indeed, one can easily imagine many other interactions beyond those mentioned above that could be explored. For example, a child's experiences of the macrosystemic forces of discrimination might influence their rapport with the researcher administering an EF measure. This may cause the child to perceive what is intended as a 'cool' measure of EF to be quite 'hot,' which in turn may elicit a different pattern of activity among the neurophysiological systems that support the child's exercise of their EF. As this example illustrates, where individual differences in children's performance on measures of EF are concerned, "the principal main effects are likely to be interactions" (Bronfenbrenner, 1979, p. 38). For a graphical summary of these factors and examples of their interactions, see Figure 1.

Implications for Future Research

Applying an ecological systems perspective to children's performance on measures of EF underscores the need to disentangle state- and trait-like contributions to individual differences on these measures. In this section, we offer an example of one way in which this could be achieved, with two caveats: first, this example is intended to be illustrative, rather than proscriptive – other approaches could be used to achieve the same end. Second, the approach outlined in this example poses certain challenges, which we discuss in greater detail below.

An Approach to Disentangling State- and Trait-Like Performance

In this example, we are interested in disentangling state- and trait-like contributions to individual differences in performance on a measure of one domain of EF (working memory) among young children. We are indexing children's working memory using the longest string of digits recalled on a backwards digit span task. We administer the task on four days at approximately equal intervals over the course of a two-week period; accordingly, each child in our sample would have a working memory score at four time points (see Figure 2).

For each child, performance on the task at any one of these time points corresponds to their state-like working memory at that point in time; each child's performance across time points corresponds to our best estimate of their trait-like capacity for working memory, within the limitations imposed by the available data. Figure 2 displays state- and trait-like working memory, as well as the discrepancy between them at each point in time. Although in this example we have used the mean over time as an index of trait-like capacity, in practice we could select from a variety of indices (e.g., the sum).

Given that our data feature four measures of working memory nested within each child, we can disentangle state- and trait-like contributions to performance on the digit span measure by applying a hierarchical or multilevel modeling approach (Raudenbush & Bryk, 2002). Conducting a random effects analysis of variance (ANOVA) would allow us to partition the overall variance in performance into its state-like (intra-individual) and trait-like (inter-individual) components. The proportion of variance accounted for by intra-individual factors would correspond to fluctuations in state-like performance across all individuals in the sample; the proportion of variance attributable to inter-individual factors would correspond to individual differences in trait-like EF.

Extensions of the Multilevel Modeling Approach

Extending this approach would allow us to address a number of questions about individual differences in children's performance on measures of EF. First, we could examine how the degree of intra-individual variability in performance differs across children. Although there are many ways to accomplish this, one approach would be to estimate the slope of the line of best fit to each child's data, and then calculate the cumulative deviation from that slope (e.g.., the pooled residuals) for each child. The cumulative deviation would represent the correspondence between state- and trait-like EF for each child, allowing for the examination of individual differences in this correspondence and, thereby, the extent to which state-like performance at a given point in time is a valid index of trait-like capacity for a given child.

We could then seek to explain these *inter*-individual differences in the degree of *intra*-individual variability in performance over time by collecting data on environmental factors that we expected to contribute to these differences prior to administering the EF measures. For example, we might hypothesize that children from homes in which there is a higher level of chaos would exhibit higher levels of intra-individual variability in their performance on our working memory measure. To test this hypothesis, we could administer a measure of household chaos (e.g., the Confusion, Hubbub, and Order Scale, or CHAOS measure; Matheney et al., 1995) prior to administering the digit span task and then examine the covariation between CHAOS scores and intra-individual variability in performance on the digit span task. A similar approach could be employed to examine and potentially account for other factors that might contribute to intra-individual variability in performance over time. For example, administering a measure of persistence (e.g., a puzzle task; Glass & Singer, 1972) prior to administering the digit span task would offer insight into how this inter-individual factor contributed to variability on this measure.

Alternatively, we might collect repeated measures data about more specific factors that would covary with the overall level of household chaos. For example, we might collect data on the quantity and quality of children's sleep the night before each day that the digit span was administered. With data on sleep and digit span task performance available at each time point, sleep could enter our multilevel model as a time-varying covariate, which would allow us to examine how intra-individual variability in children's sleep covaried with state-like performance on the digit span task. Our hypothesis might be that lower quality sleep on the night before testing would predict poorer task performance on the following day.

The multilevel modeling approach would also allow us to examine *inter*-individual differences in trait-like EF after controlling for factors (e.g., sleep) that might contribute to *intra*-individual variability in state-like performance. For example, we might hypothesize that older children (e.g., approximately 6 years of age) would consistently perform better on our digit span task than younger children (approximately 4 years). To test this hypothesis, we would add child age to our model as a time-invariant covariate, while retaining sleep from our previous model as a time-varying covariate. If our hypothesis was correct, we would expect to observe a positive, statistically-significant effect for age, indicating that older children exhibit better performance on the digit span task across the four time points at which it was collected, after accounting for intra-individual differences in performance and the influence of sleep on those differences.

We could also assess how factors at different levels of the developmental ecology interact to contribute to individual differences in children's state- and trait-like performance on measures of EF. Returning to our previous model, we might be interested in how child age operates in tandem with the quality of children's sleep to predict performance on our measure of working memory over time. This question could be addressed by introducing a cross-level interaction between age and sleep quality. We might hypothesize that: 1) while poorer quality sleep is associated with poorer task performance across time points (which in the context of our study, represents trait-like working memory), this is especially so for younger children; and that 2) the impact of sleep quality at a particular time point is greater among younger children, such that the same level of intra-individual variability in sleep quality corresponds to a higher degree of intra-individual variability in state-like performance on the digit span task among younger children.

Finally, we could extend the model to accommodate data on measures of EF collected at multiple time points *and* across multiple ages (such that the k^{th} time point was nested within j^{th}

age for the i^{th} child; Raudenbush & Bryk, 2002). Intra-individual differences across the *k* time points would still represent state-level variation in performance, and data collected at or across these time points could be included as time-varying or invariant covariates (respectively) to account for this variability, as described above. However, intra-individual variability in performance across the *j* ages at which data were collected would be attributable, in part, to development, and, in part, to factors that might vary over time and were not accounted for by covariates included at the k^{th} level of the model. Adding additional covariates at the j^{th} level of the model to these k^{th} level covariates would allow for the disentangling of state-level variations in performance across micro- and mesotime (corresponding to the k^{th} level and j^{th} levels of our model, respectively; Bronfenbrenner & Morris, 2006) from trait-level individual differences in performance. This approach would provide considerable insight into the development of EF in children, and would represent a strategy more closely aligned with perspectives that conceptualize EF *in situ*: as skills that are deployed in particular situations to achieve specific goals, and that develop alongside children's broader understanding of the world, as influenced by each child's unique sociocultural context (Doebel, 2020; Miller-Cotto et al., 2022; Munakata & Michaelson, 2021; Yanaoka et al., 2022).

Challenges Inherent in the Proposed Approach

The approach described above would present a number of challenges; chief among these would be the requirement to collect repeated measures of EF over time, with the potential to increase the duration (and budget) for data collection by a multiple approximating the number of repetitions. Given this, it is important to carefully consider the optimal number of times to administer a set of measures. If time and money were no object, one might be tempted to collect data very frequently (e.g., daily) over a short span of time (e.g., two weeks), in order to maximize the potential correspondence between children's state-like performance and their underlying trait-like EF capacity. However, in practice researchers' time and money are finite, and beyond a certain point the marginal benefit of one more repeated measure may not justify the associated marginal cost.

That cost is borne, in part, by the children and families participating in data collection, and asking children to complete many repeated measures may strain both their endurance and their families' patience. Taxing children's endurance through the administration of many repeated measures also has the potential to introduce instrumentation effects, wherein children's performance declines over time as the request to complete the same task becomes boring and, ultimately, frustrating. Alternatively, instrumentation effects may result in some children's performance improving over time, even for measures that randomize the specific content of each trial, as they become more familiar with the format and requirements of the measure. A large number of repeated measures also increases the likelihood that the residuals, which represent the deviation of state-like performance at a given point in time from underlying trait-like EF, may not be distributed in a uniform fashion across time points. As the number of repeated measures increases, it becomes more likely that residuals closer together in time (e.g., the residuals at time points 1 and 2) will be more similar than those for time points that fall further apart (e.g., time points 1 and 4).

Fortunately, the multilevel modeling approach described above offers ways to accommodate both instrumentation effects and serial dependency among the residuals. Testing for instrumentation effects can be accomplished by estimating the slope of state-like performance over time. If this estimate is not significantly-different from zero, we can conclude that instrumentation effects are not present at the level of the sample. A significant, positive slope for the sample would suggest practice effects are present, whereas a significant, negative slope would suggest that children's performance declines over time, perhaps as a result of fatigue or boredom. Of course, it is possible that inter-individual differences in these slopes would be observed, with some children exhibiting a positive slope and others a negative slope; this can be accommodated incorporating a random slope term into the multilevel model and then adding additional data (e.g., regarding task persistence) to account for these differences.

Implications for Future Evaluations of Educational Interventions

One area of applied developmental research in which disentangling state- and trait-like performance is particularly important is in the evaluation of educational interventions designed to foster children's EF. As a recent review demonstrated, these interventions abound, and range from relatively brief, computer-based training programs to more extended interventions that use exercise, mindfulness practices, or school-based curricula (Diamond & Ling, 2020). Given the predictive validity of EF for subsequent academic outcomes, educational researchers and practitioners are keenly interested in knowing which interventions foster children's EF. This question is often addressed by randomly assigning some children to receive the intervention (thereby placing them in the treatment group) while others do not (the control group), and then administering measures of EF to children in both groups prior to and following the receipt of the intervention by children in the treatment group. By applying a differences-in-differences approach, researchers can compare the degree of change in EF among children assigned to each group over the same period of time. If children who received the intervention exhibit a significantly-greater degree of positive change than their peers, it is typically interpreted as evidence that the intervention is causing EF to improve at a rate that exceeds that associated with development.

This interpretation and the approach upon which it is based invokes two assumptions. The first of these is that a child's performance on a measure of EF at a given point in time (e.g., pre-intervention) is a valid index of trait-like EF. Applying an ecological systems perspective suggests that this assumption is incorrect: a child's performance at a given point in time indexes their state-like EF, which reflects their trait-like EF to an unknown degree. Collecting repeated measures of EF pre- and post-intervention would offer a better estimate of children's underlying EF capacity. The question is, how many repeated measures should be collected?

The answer depends on finding the optimal balance between the marginal benefits and costs of an additional measure. In the context of an educational evaluation, part of the costs are borne by the school and students in the form instructional time lost to testing. Managing these costs may require administering repeated measures of EF during "program time," rather than "school time," though this may not appeal to program developers. When negotiating the number of repeated measures to be administered, researchers should bear in mind that even a small number of repetitions pre- and post-intervention would allow researchers to examine intra-individual differences in state-like performance, and, in combination with other data, would also allow researchers to identify and account for factors that might otherwise bias estimates of intervention effects.

A second assumption of the differences-in-differences approach to evaluating EF interventions is that children's performance on pre- and post-intervention measures are equally-valid indices of trait-like EF, such that change in trait-like capacity can be assessed by comparing change in state-like performance on measures of EF administered pre- and post-intervention. Again, ecological systems theory suggests that this assumption is incorrect, but the logic of randomized designs dictates that the environmental factors that may influence state-like performance are distributed such that they do not bias estimates of the intervention's effects.

However, one can readily imagine scenarios in which these factors are not distributed randomly. For example, a researcher may be hard-pressed to administer measures of EF to students in both study conditions before the intervention begins. They may therefore administer the measures of EF to children in the treatment group slightly earlier in the school year, and then move on the control group once the treatment-group students are receiving the intervention. As a result, children in the treatment group will be earlier in the process of their transition to school when they complete their pre-intervention measures, which may influence children's state-like performance on these measures. For example, children exhibit higher levels of HPA-axis activity earlier in the process of their transition to school (see Parent et al., 2019 for a review), and, as noted above, higher levels of HPA-axis activity are associated with poorer performance on measures of EF in children (Blair et al., 2005). Therefore, administering measures slightly earlier in the school year to children in the treatment group may adversely impact their state-like performance on the pre-intervention measures of EF, while leaving their post-intervention performance relatively unperturbed, leading to biased estimates of the intervention's effects.

The Micro- and Mesosystems of the Educational Environment

When evaluating educational interventions designed to foster children's EF, it is important to consider factors in the microsystem of the educational environment that may impinge upon performance on measures of EF. Some of these factors may be stable over time; one such example is the overall quality of instruction in children's classrooms, absent the intervention. If an intervention's theory of change is that a relatively brief educational intervention can improve children's trait-like EF, then surely any evaluation of that same program should allow for the possibility that children's more extended experience in the classroom would impact EF when examining intervention effects.

However, other factors in the educational environment may fluctuate over time, contributing to intra-individual variability in state-like EF performance and inter-individual differences in the degree of that variability. If data are collected in children's classrooms, a number of time-varying factors including noise, distractions, interruptions, and teacher absence could contribute to intra-individual variability in performance on measures of EF. Classroom environments that are more chaotic will, by definition, feature higher levels of fluctuations in these and other time-varying factors, again underscoring the role of environmental chaos as a super-ordinate environmental factor with the potential to permeate multiple microsystems and thereby contribute to intra-individual differences in performance on measures of EF. That said, we would not expect the contributions of environmental chaos in the school microsystem to influence intra-individual variability in the same way for all children, but rather for that influence to vary contingent upon factors at the same or different levels of the ecology. For example, a child who is temperamentally prone to anxiety may exhibit a higher degree of intra-individual variability in their state-like performance on measures of EF in a chaotic school environment than a child who experiences lower levels of anxiety.

Ecological systems theory would also recommend collecting data about factors located in the mesosystem formed by the intersection of the child's home and school environments, as these data would provide important information for understanding intra-individual differences in state-like performance on EF measures. For example, one intersection between the home and school environment is the school drop-off routine, whether this occurs by bus, car, or other means. A serious disruption in these routines may discomfort a child throughout the school day, which could, in turn, adversely impact the child's state-like performance on measures of EF. Moreover, the same degree of disruption would not be expected to have the same impact on state-like performance for all children; rather, we would anticipate that inter-individual differences in this impact would vary as a function of other factors. State-like performance for a child predisposed to anxiety, for example, might be impacted more adversely by a disruption in drop-off routine.

Conclusion

In this paper we applied an ecological systems perspective to understanding children's performance on measures of EF. We argued that the application of this perspective underscores the need to disentangle state- and trait-like contributions to individual differences in performance on these measures, and offered one approach that researchers might employ in future studies to accomplish this. We are well aware that the core of this approach – collecting repeated measures of EF over relatively brief periods of time – presents a number of challenges, but we believe that the effort invested in overcoming these challenges is well-spent, given that it has the potential to address fundamental and long-standing questions about the development of EF in children.

For example, it is well-established that children's performance on cognitive-behavioral measures of EF correlates only modestly with parent ratings on questionnaires about children's EF (cf., Toplak et al., 2013). While there are many explanations for these modest correlations, one may lie in the differential degree of stability in measures of performance and questionnaire ratings, which, in turn, partially reflects divergent temporal dynamics of data collection for cognitive-behavioral measures (which lasts for minutes) and parent ratings (which typically reference weeks or months of children's behavior). With repeated administrations of cognitive-behavioral measures and questionnaires, this hypothesis about the source of the discrepancy between performance on cognitive-behavioral measures and questionnaire ratings would be open to empirical investigation.

Ultimately, we may find that most children display a modest degree of intra-individual variability in their state-like performance on measures of EF, and that therefore a measure at any given point in time is a reasonably valid assessment of a child's trait-like capacity for EF. In this case, we could continue to conduct research more or less as we have done to date, but with a renewed confidence in the validity of our measures. However, we instead may find that at least some children exhibit substantial variability in their state-like performance, and that for these children it is important to understand and account for factors that contribute to this variability in both basic and applied research into the development of EF in children.

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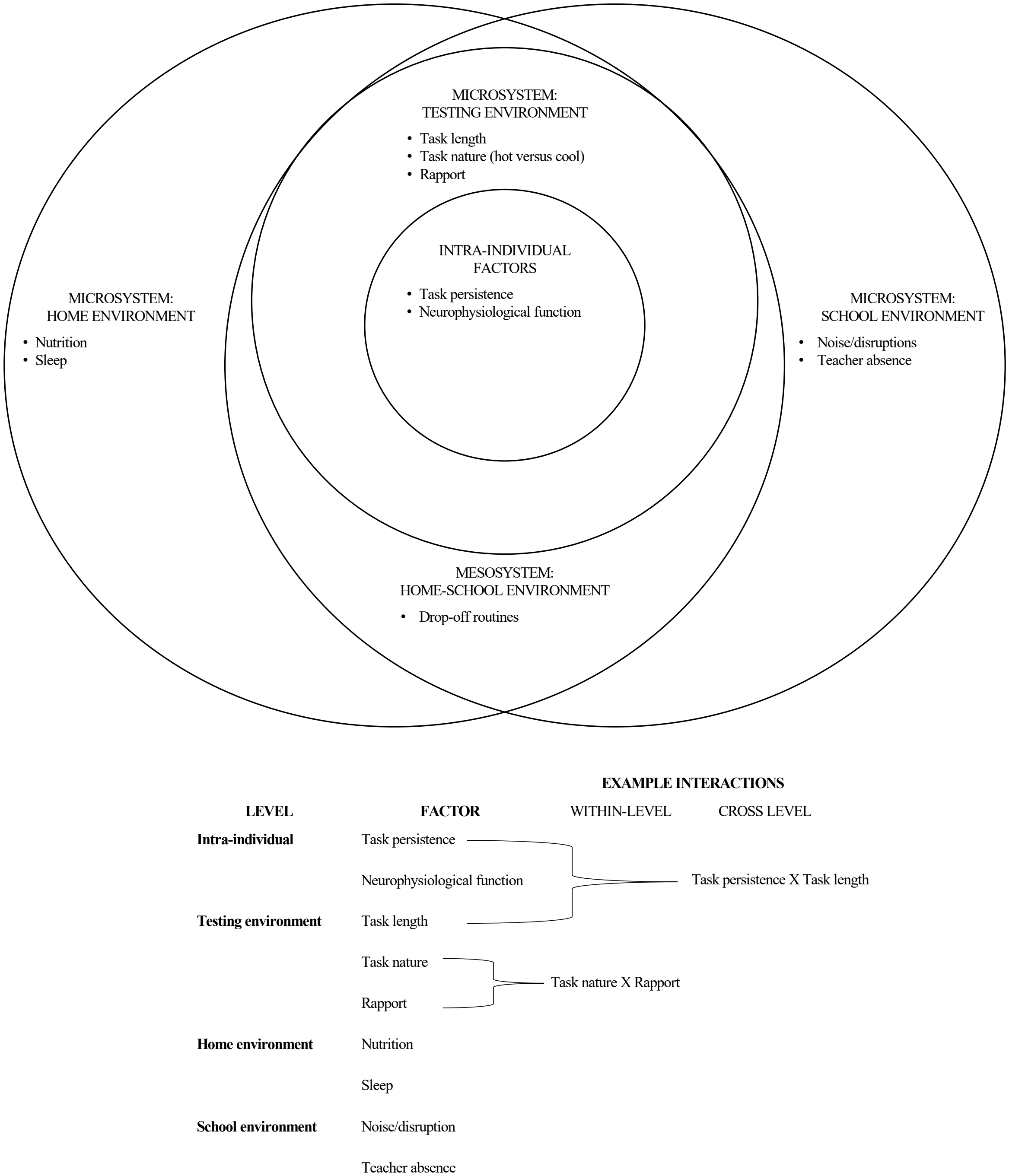

Figure 1. A summary of factors discussed in the text that may influence state-like performance on measures of EF, with examples of select within- and cross-level interactions. Note that the factors listed under the home environment (nutrition and sleep) refer to the factors that may influence a child's nutrition and sleep status at the time of testing.

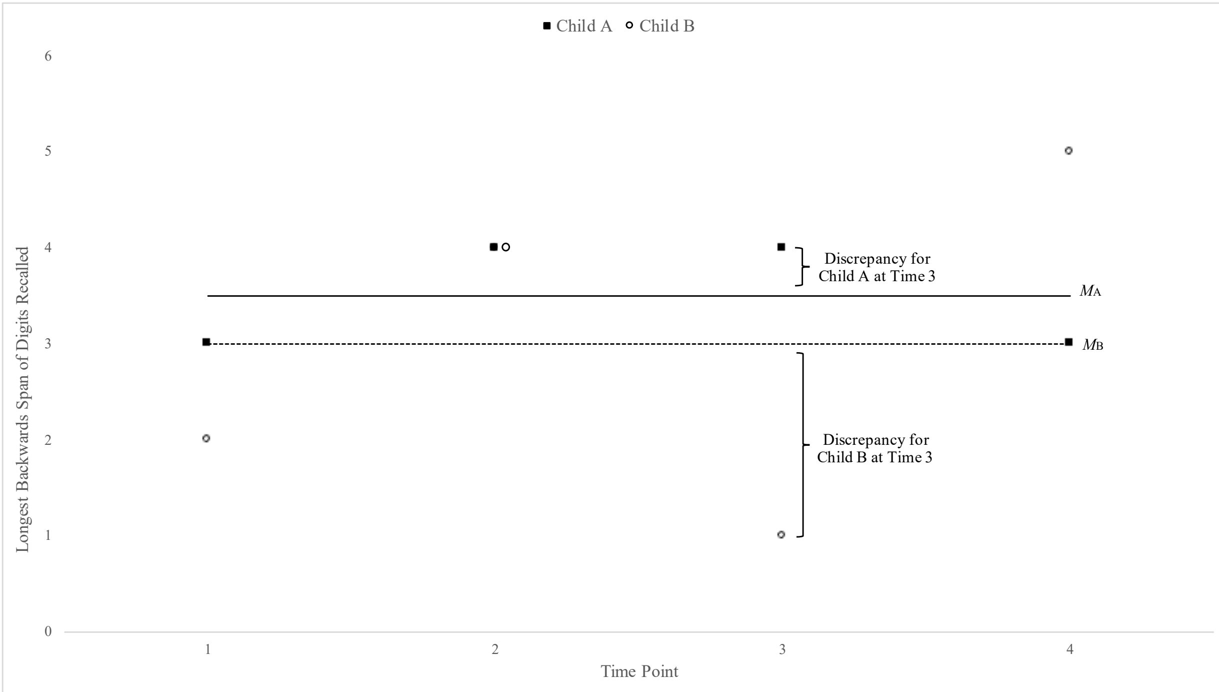

Figure 2. An example of data from two children that would be collected according to the approach described in the text.

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