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Cognitive Variability

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Cognitive variability reflects the instability of our cognitive abilities. Our ability to reason, respond, and remember fluctuates within the same person across seconds, minutes and hours, and even days, weeks, and months. Imagine two children, Charles and Ada, performing a cognitive task, such as remembering up to 10 digits. Across trials, they may have the same average performance, but the *variability* in their cognitive performance is very different, with Charles having pronounced peaks and troughs and Ada consistently scoring similarly. Cognitive variability refers to the degree to which the same individual shows differences in cognitive performance across different moments (e.g., trials or days) or different contexts. Such cognitive variability, or *cognitive fluctuation*, is familiar to every person. Cognitive abilities wax and wane across time and environment, affected by sleep, mood, and circumstance. Cognitive variability as a scientific construct remains relatively underexplored compared to the more well-established construct of mean performance. This neglect of variability in favor of the mean is a mistake. Cognitive variability affects how we manage our day-to-day challenges; it is clearly distinct from mean performance, with separate causes and consequences, and offers a source of unique insights into cognitive performance and development over time.

History

Over a century ago, Raymond [Dodge \(1924\)](#) argued in the journal *Science* that variability in performance is just as real, and worth studying, as average performance. Dodge showed how understanding variation in behavior (unlike physical measurements) around a hypothesized true value is a crucial goal rather than simply error to adjust for. This sentiment was echoed by Clark [Hull \(1943\)](#), who even stated that variability in performance is the central distinction between biological humans and inorganic machines. A decade later, [Fiske and Rice \(1955\)](#) presented a more rigorous examination of (psychological) variability, distinguishing between systematic (e.g., periodic) and unsystematic variability, and examined the role of internal and external factors. John [Nesselroade \(1991\)](#) gave the first fully modern treatment of cognitive variability, discussing it in the broader context of human lifespan development and setting out a methodological agenda to measure variability rigorously.

Core concepts

What is cognitive variability?

Cognitive variability reflects differences in performance on a cognitive task across different occasions, ranging from trial to mean performance on different occasions (e.g., days, months, seasonal, or different settings). The recent increase in availability of high temporal resolution data that samples individuals more frequently (e.g., many trials within a session or multiple measurements on consecutive days) alongside quantitative innovations have opened up this fascinating construct to rigorous empirical definition and investigation, offering a range of empirical discoveries and open questions sure to shape the field for decades.

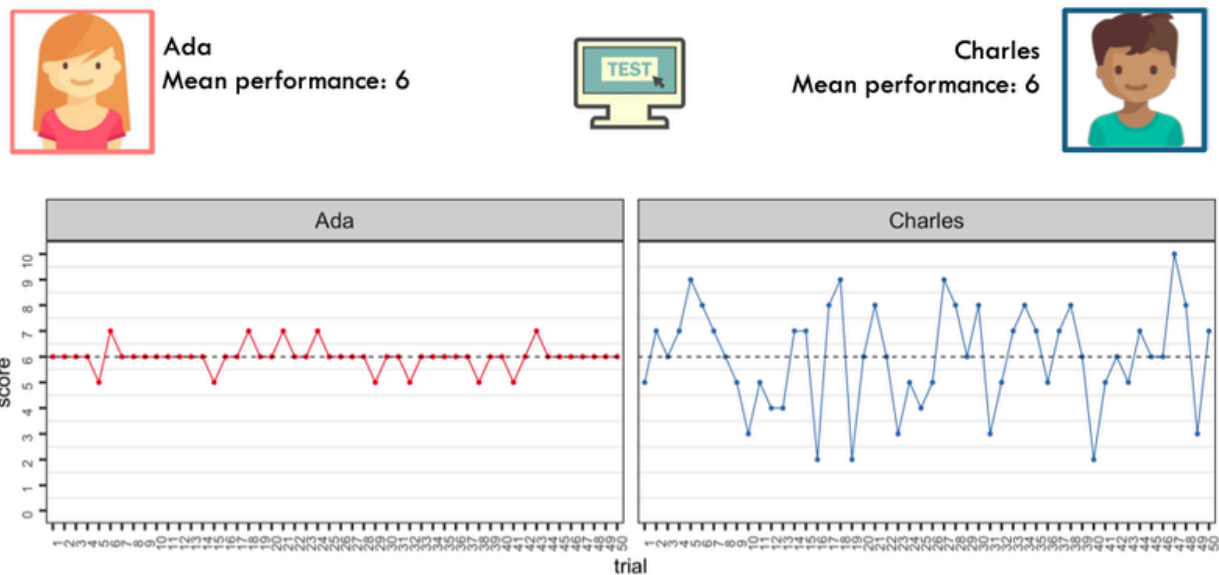


Figure 1

Two hypothetical children with the same mean performance (6) but with substantial differences in cognitive variability (Charles is much more variable than Ada).

Although variability is sometimes used to refer to differences between individuals (more commonly referred to as “individual differences”) or to differences in mean performance between different task domains (to assess relative discrepancies in performance), we prefer individual differences and dispersion for those constructs instead. The cognitive task used can vary from simple (e.g., a basic reaction time task) to cognitively challenging (working memory or abstract reasoning). The measure to quantify variability can also vary between (or within) tasks. Although reaction time is commonly used, measures can be any (ideally continuous) measure of performance, including accuracy (spatial or directional) or capacity (how many questions on a test are answered correctly).

How to quantify variability?

Cognitive variability is easy to explain but hard to quantify. Simple methods include the intraindividual standard deviation, residual standard deviation from linear models, or the (root) mean square of successive differences, which can be computed deterministically from trial sequences. However, known shortcomings include conflation with the mean and an outsized impact of trends and outliers (cf., [Mestdagh et al., 2018](#)). More recent innovations include the relative variability index ([Mestdagh et al., 2018](#)), residual variability from a dynamic structural equation model ([Hamaker et al., 2021](#); [Judd et al., 2024](#)), location scale models (e.g., [Hedeker et al., 2021](#)), or leveraging structural equation modeling to estimate variability as a fully latent variable ([Feng & Hancock, 2024](#)). Other avenues include drift diffusion or ex-Gaussian models, which allow for the estimation of (noisy) information accumulation and

(attentional) lapses as drivers of variable performance. Quantifying variability is an active area of research and application. Each of these methods have strengths and weaknesses and should be selected based on a series of considerations including the fit to the research question and the nature of the data.

Causes and consequences of variability

Although rigorous empirical investigations of variability are still relatively recent, several robust findings have emerged. Between individuals, existing evidence suggests that individuals with greater inattention (e.g., [Aristodemou et al., 2024](#)) and more mind wandering (e.g., [Seli et al., 2013](#)) tend to show greater cognitive variability. Moreover, greater variability has been linked with neurodevelopmental disorders including attention deficit hyperactivity disorder (ADHD) and (less clearly) autistic spectrum disorders ([Karalunas et al., 2014](#)). In fact, [Aristodemou et al. \(2024\)](#) found that cognitive variability is associated with the dimension of inattention but not hyperactivity, demonstrating specificity within ADHD symptomatology. At the neural level, greater myelination of axons (myelin is a fatty tissue that wraps around axons and functions as insulation, supporting more rapid, reliable signal transmission between neurons) has been associated with less variability in reaction time performance, likely because of less signal transmission loss (e.g., [MacDonald et al., 2006](#)).

Within individuals, day-to-day variation in sleep and mood are linked with day-to-day changes in performance, more so in some areas than others ([Neubauer et al., 2019](#)). Across the lifespan, there is a decrease in variability across childhood into adolescence followed by an increase in variability in old age, with an especially pronounced increase in variability in atypical (e.g., dementia) aging ([Hultsch et al., 2000](#); [Ram et al., 2005](#)).

Questions, controversies, and new developments

Although much progress has been made on understanding cognitive variability, many questions remain. One avenue for both fundamental and applied work is to decide on the most suitable measure to capture variability. A range of measures and implementations exist—their relative performance and conceptual implications are still being explored.

Second, what are the (metabolic) costs of stability? Although it is easy to imagine scenarios in which excessive variability is risky, it is equally easy to overlook the costs of excessive stability (e.g., see [Pfeffer et al., 2021](#)) or the benefits of variability when dealing with variable challenges in a dynamic world (e.g., [Vaughan & Birney, 2023](#)). Does this imply an (evolutionary) tradeoff between stability and flexibility and that individuals simply vary in terms of their optimization of this tradeoff?

Finally, most of the empirical work has suggested that greater cognitive variability is generally associated with negative outcomes, such as (pathological) aging, inattention, and a lack of expertise. However, it is plausible that certain types of variability, or variability in certain contexts, is not only adaptive but necessary [see [Rational Analysis](#)]. A key open question is how to isolate such good or desirable variability: Which tasks, contexts, and measures allow such variability to shine?

Broader connections

Studying cognitive variability has pushed methodological boundaries, opened new empirical frontiers, and provided a richer empirical and conceptual view of cognitive performance and development as a dynamic system [see [Complex Dynamical Systems](#)]. One particular avenue for broader connections is with educational technology. Digital tools for learning are now all but ubiquitous in Western education systems, but the richness they offer has not been fully leveraged, either scientifically or translationally. Not only do such platforms allow for greater sample sizes and temporal richness to enable a quantitative handle on variability but they offer the promise of ecological validity of real performance fluctuation in the classroom (e.g., [Vaughan & Birney, 2023](#)) and a way to address how easily measurable factors such as background noise may affect day-to-day or session-to-session differences in performance ([Coolen et al., 2024](#)) [see [Citizen Science](#)].

A second broader connection is with (pharmacological) intervention. The majority of the empirical work on cognitive variability has been observational, relying on either purely descriptive characteristics or the a priori plausibility of (causal) mechanisms. However, it has been shown that pharmacological intervention using (for instance) methylphenidate to decrease ADHD symptomatology has pronounced effects on response time variability, even though that was not the primary target ([Kofler et al., 2013](#)). Future experimental manipulations will allow cognitive scientists to tease apart the efficacy (or lack thereof) of behavioral manipulations (including neurofeedback or incentivization) to affect variability. Alternatively, experimental manipulation of brain processes using transcranial magnetic stimulation or transcranial direct current stimulation could be used to disrupt (or boost) brain processes thought to be involved with variability. Such approaches will allow the field to better triangulate the diverse mechanisms underlying individual differences in intraindividual cognitive variability.

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