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Ability vs Adaptability: What Dynamics Reveal

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Abstract

Stable trait estimates from sequential task performance fail to separate ability from adaptability: the real-time recalibration of cognitive control parameters that improves execution without acquiring new knowledge. This conflation biases ability estimates. We develop a tractable framework measuring adaptability through trial-by-trial performance dynamics in mathematical cognition tasks. Across large datasets (N>10,000), adaptability strongly predicts math achievement and is uncorrelated with traditional ability measures, establishing it as an independent construct critical for understanding individual differences in cognitive performance.

Keywords: Ability; Adaptability; Math Cognition

Introduction

Cognitive assessments make a critical assumption: performance reflects stable traits, while trial-by-trial data generation only produces serially correlated measurement noise. This assumption is empirically and theoretically untenable. Even in simple tasks where rules remain constant and difficulty is randomized, performance systematically changes across trials (Figure 1). These dynamics reflect *adaptability*: the real-time recalibration of cognitive control parameters (attention, strategy, motor execution) improving performance without acquiring new knowledge or restructuring cognitive representations. Traditional static measures confound this dynamic optimization with stable processing capacity, producing biased estimates of individual capability.

Our central hypothesis is that ability and adaptability are distinct factors predicting cognitive task performance. Consider a professional footballer adjusting coordination for subtle shifts in turf texture and ball pressure, or a baseball player entering batting practice to tighten timing sensitivity. These are acts of adaptive optimization within known frameworks, not relearning of mechanics. Similarly, in cognitive tasks, individuals optimize execution as trials unfold. For a constant level of underlying processing capacity, this adaptation is the sole source of improved performance (Figure 1). If static measures attribute all performance variance to stable traits, they necessarily mischaracterize individual differences.

This paper develops a tractable statistical framework to decompose task performance into ability and adaptability components, then demonstrates that adaptability, measured through trial-by-trial dynamics, predicts formal math achievement independently of, and often more strongly than, conventional static measures like the Weber fraction. Using two large-scale datasets (over 10,000 adults with SAT scores (Halberda et al., 2012) and 243 school-age children with standardized assessments (Alonso-Diaz et al., 2025)), we show that adaptability exhibits distinct developmental patterns and accounts for achievement variance that static approaches miss entirely.

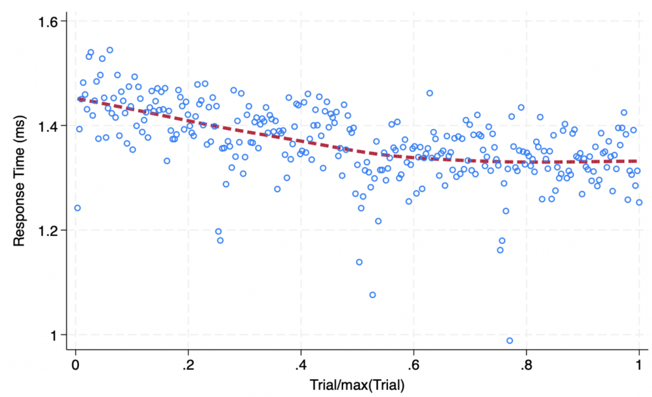

Figure 1: Behavior in a non-symbolic number comparison task evolves systematically across trials (pick the larger cloud of dots in a pair). Red dashed line shows the adaptability trend obtained with standard non-parametric methods (Hodrick-Prescott filter). This pattern emerges despite randomized difficulty and minimal learning requirements.

Ability versus adaptability. Ability reflects stable, generalizable traits enabling consistent execution across contexts. Adaptability reflects the capacity to adjust performance as situational demands unfold. Empirical evidence shows that standard measures confound them. Bagaini et al. (2025) found that risk preference scores appear trait-like but vary with task framing, indicating contextual dependence. Cooper et al. (2015) demonstrated that motivational framing alters decision strategies, underscoring adaptability's situational specificity. While ability captures broad competence, adaptability accounts for dynamic responsiveness: the capacity to regulate performance as conditions shift.

These dimensions differ systematically across multiple literatures. Ability reflects stable, trait-like characteristics that remain relatively fixed in the short term and are captured by static metrics (Heckman & Zhou, 2025; John et al., 1988). Adaptability, by contrast, is dynamic and context-dependent,

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evolving through performance history and feedback (Bagaini et al., 2025; Cooper et al., 2015; Eldar et al., 2018). Traditional measurement approaches conflate these constructs because static summaries treat temporal variation as noise rather than systematic adjustment (Fortenbaugh et al., 2015; Kosciessa et al., 2024; Rutledge et al., 2014). Rather than offering a definitive taxonomy, we highlight that this distinction appears across neuroscience, behavioral economics, and decision-making research, while allowing for interactions between ability and adaptability. Critically, we later demonstrate that in mathematical cognition tasks, these constructs are empirically independent.

Although adaptability has been studied in neuroscience (Eldar et al., 2018), decision-making (McDougle et al., 2016), and behavioral economics (Braun et al., 2009; Rustichini et al., 2017), our contribution is threefold. First, we adapt well-established, interpretable methods for extracting adaptability from trial-by-trial dynamics in standard cognitive tasks. Second, we demonstrate its critical role in predicting achievement in abstract-symbolic domains (mathematics). Third, we show that adaptability is uncorrelated with traditional ability measures, establishing it as an independent dimension of cognitive competence rather than a methodological refinement.

We exploit the systematic change in accuracy and response times across trials, even when task difficulty is randomized: a behavioral signature of adaptability (Figure 1). This trend reflects optimization of execution since the task requires minimal explanation (pick the numerically larger cloud of dots). The specific mechanism (whether attention allocation, confidence calibration, motor preparation, or strategy adjustment) is not critical for our framework. Our method merely exploits the existence of smooth performance change to estimate adaptability strength.

The implications extend beyond mathematics. In any domain where behavior changes with task structure, inference should incorporate temporal dynamics. We align with a recent shift in cognitive science: interpret dynamic performance not as confound but as signal (Urai, 2025). Cognitive performance is rarely static. Even absent new learning, behavior adjusts. Treating these adjustments as noise rather than information fundamentally mischaracterizes human cognition.

Adaptability in Non-Symbolic Tasks: An Illustration

Why should optimizing performance on a simple dot comparison task predict success in algebra? The link between non-symbolic numerosity perception (estimating dot quantities) and formal math achievement is well-established (Chen & Li, 2014; Dillon et al., 2017; Halberda et al., 2008, 2012), but the mechanism at play remains contested (Bugden et al., 2021; Price et al., 2012; Szkudlarek & Brannon, 2017). We suggest that this link reflects adaptability in cognitive compression rather than perceptual precision alone.

Symbolic math requires that perceptual inputs (e.g., Arabic numerals) be transformed into computationally tractable formats. For example, the numerical quantity represented may be compressed on a logarithmic scale or encoded into manageable categories (Schley & Peters, 2014). Critically, individuals differ in their ability to compress information as well as how efficiently they adapt to growing demand for increased compression: their innate ability and their capacity to respond to a changing environment. That these dimensions are empirically independent (Figure 2) suggests they reflect distinct cognitive mechanisms.

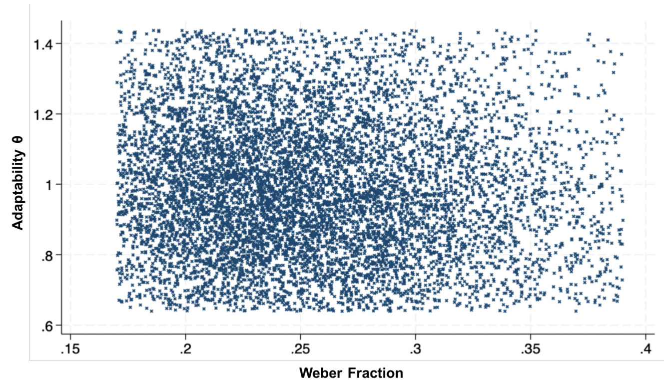

Figure 2: Independence of peer-relative ability and Weber fraction ($r \approx 0.02$). Our adaptation-adjusted ability measure is essentially uncorrelated with traditional static measures, establishing them as orthogonal dimensions of cognitive performance. This independence motivates the hypothesis that non-symbolic tasks capture dynamic optimization capacity, not merely stable perceptual traits.

The salience of the latter is clearest for working memory, a key bottleneck in mathematical reasoning (Ashcraft & Krause, 2007; Sims et al., 2012). Working memory is both capacity-limited and information-constrained. As individuals engage with increasingly complex mathematical problems, adaptable compression reduces the "bits" required to represent numerical information. This compression frees up working memory that, in turn, allows the individual to manipulate symbols more effectively. Consequently, a more adaptable individual is more effective at engaging in the cognitively demanding tasks required to solve a mathematical problem, regardless of her intrinsic ability.

Non-symbolic tasks reveal this adaptability directly. When participants adjust their performance across trials (Figure 1), they illustrate increasingly efficient coding of numerical quantities. This recalibration operates as a preprocessing layer: compressing input before symbolic computation begins. Individuals who adapt compression efficiently in simple dot tasks should adapt it efficiently in complex symbolic math, where working memory constraints are most binding.

This reframes the numerosity-math link. The predictive power of dot comparison tasks stems not from measuring a stable perceptual trait, but from capturing dynamic optimization capacity (Figure 2). In domains where cognitive resources are finite and demands are sustained, adaptability is the mechanism by which individuals overcome rising cognitive constraints.

Methods

We obtained behavior on non-symbolic number tasks (Figure 3) and symbolic mathematics from two publicly available datasets in the Open Science Framework. The first dataset includes over 10,000 adults who completed multiple trials of non-symbolic number comparison tasks (Figure 3A) and self-reported their SAT scores (osf.io/bw6jr/). Self-reports were validated by the original authors through statistical analyses (Halberda et al., 2012).

The second dataset includes 4th and 6th grade Colombian students who completed both tasks (Figure 3) and a national standardized math test (osf.io/preprints/psyarxiv/z492x_v1). The data also included reaching metrics, mouse velocity, and curvature. Both datasets contain additional cognitive and demographic information (see links for details).

For full details on the number of trials, timing parameters, difficulty distribution, feedback structure, randomization procedures, operationalization of behavioral measures (RT, velocity, curvature, AUC) and preprocessing, see the references above.

Data analysis

We treat trial-by-trial data as time series to normalize the non-identification between ability and within-session dynamics by defining a cohort-level adaptation trajectory and measuring peer-relative performance. Each participant i has stable ability $\theta_i \in \mathbb{R}$ and demographic characteristics $\omega_i \in \Omega \subset \mathbb{R}^n$. Experiment trials are indexed $t = 1, 2, \ldots, T$. For each participant, we observe $L > 0$ performance variables (response times, movement times, velocity, curvature, cumulative accuracy). The data structure is:

$$D \equiv \left\{\omega_i, \left\{\{y_{i\ell t}\}_{\ell=1}^{L}\right\}_{t=1}^{T}\right\}_{i=1}^{N}.$$

Estimation of Peer-Relative Ability

Model. We decompose performance as:

$$y_{i\ell t} = \theta_i \cdot \tau_{\ell t} + \epsilon_{i\ell t} \tag{1}$$

where θ_i is individual ability (stable processing capacity), $\tau_{\ell t}$ is the common adaptability trend (within-session optimization trajectory), and $\epsilon_{i\ell t}$ is noise. This multiplicative form allows smooth within-session dynamics to scale with stable between-subject differences, yielding a peer-relative ability index after normalizing by the cohort trajectory. Additive forms are possible, but not critical for the current effort of demonstrating that an adaptability metric carries relevant information for real world performance.

Identification. Ability and adaptability are not uniquely separable from sequential performance without normalization: scaling θ_i and inversely scaling $\tau_{\ell t}$ yields identical fitted values. We therefore define $\tau_{\ell t}$ at the cohort level (estimated from cohort-average dynamics), and interpret $\tilde{\theta}_i$ as relative ability within cohort.

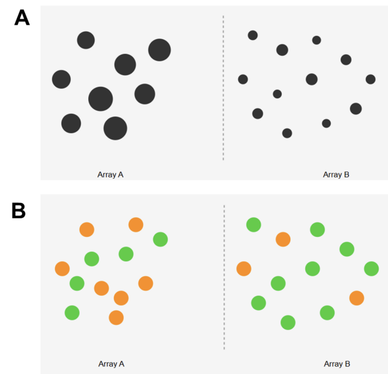

Figure 3: Non-symbolic number tasks. A. Participants briefly view two dot arrays and indicate which side contains more dots (side counterbalanced). B. Participants briefly view dot arrays varying in color proportion and indicate which side has the larger proportion of a target color (side counterbalanced).

Estimation strategy. To estimate ability θ_i net of common adaptability dynamics, we first extract the cohort-level trend $\tau_{\ell t}$ using a Hodrick-Prescott (HP) filter applied to age-cohort-averaged performance. The HP filter isolates smooth within-session dynamics without parametric assumptions, penalizing rapid trend shifts through parameter λ. We explored $\lambda \in [1{,}600, 10^9]$ and found stable results; we use $\lambda = 10^6$ to preserve mid-scale temporal structure while suppressing noise.

The HP filter applied to cohort averages yields $\hat{\tau}_{\ell t}\theta_a$, where $\theta_a \equiv \sum_{i \in a} \theta_i / n_a$ is mean ability in age group a. We then estimate individual ability as:

$$\tilde{\theta}_i = \frac{1}{T}\sum_{t=1}^{T} \frac{y_{i\ell t}}{\hat{\tau}_{\ell t}\theta_a} \tag{2}$$

We compute $\tilde{\theta}_i$ using response times as the primary performance measure; analogous results hold for other metrics. Under equation (1), this recovers $\tilde{\theta}_i \approx \theta_i/\theta_a$ (relative ability within cohort). Values $\tilde{\theta}_i = 1$ indicate performance consistent with cohort-average ability, $\tilde{\theta}_i > 1$ indicates above-average ability, and $\tilde{\theta}_i < 1$ indicates below-average ability.

Empirical validation. After removing the cohort-level within-session trajectory, residuals $\hat{\epsilon}_{i\ell t} = y_{i\ell t} - \tilde{\theta}_i \cdot \hat{\tau}_{\ell t}\theta_a$ display near-zero autocorrelation at all lags across cohorts, tasks, and metrics (Figure 5 bottom right corner), indicating that the extracted smooth component accounts for essentially all serial dependence in trial-by-trial performance. This two-component structure (smooth adaptation trajectory plus temporally uncorrelated residuals) contradicts the standard view that trial-by-trial variation is simply serially correlated measurement noise around a stable trait, and supports our identification strategy: the cohort-level trajectory captures systematic within-session dynamics without leaving behind unmodeled temporal dependencies.

Comparison to static measures. We compare $\tilde{\theta}_i$ to the Weber fraction, a traditional measure of perceptual acuity computed from aggregate accuracy across difficulty levels (Piantadosi, 2016). Lower Weber fractions indicate higher precision. Critically, the Weber fraction conflates ability with within-session dynamics by treating all trial-by-trial variation as measurement noise.

Outcome regressions. We regress math achievement (SAT math scores for adults; standardized test scores for children) on peer-relative ability $\tilde{\theta}_i$ and Weber fraction, controlling for age, gender, mean performance, and overall accuracy. Standard errors account for participant clustering where appropriate.

Results

Our central finding is that trial-by-trial dynamics contain achievement-relevant signal beyond static summaries. In children, multiple measures of within-session adaptation (RT, accuracy, movement dynamics) vary systematically with standardized math scores even when controlling for Weber fraction (Table 1). In adults, a peer-relative performance index $\tilde{\theta}_i$ predicts SAT math scores alongside standard ability proxies. Once overall accuracy is included, Weber fraction contributes little additional explanatory power, whereas $\tilde{\theta}_i$ remains predictive (Table 2).

Within-session adaptation trends vary systematically with math achievement (children)

Table 1 shows that children with above-median math scores exhibit systematically different within-session dynamics across all behavioral measures: response time trends, accuracy trajectories, movement times, velocity, and area under curve. These differences persist after controlling for Weber fraction, establishing that trial-by-trial dynamics carry information about mathematical ability that static accuracy summaries do not capture. This pattern holds across multiple metrics, demonstrating that adaptation dynamics reflect genuine cognitive processes rather than measurement artifacts specific to one variable.

Peer-relative ability adds predictive power beyond Weber fraction (adults)

In the adult dataset (N>10,000), peer-relative ability $\tilde{\theta}_i$ predicts SAT math scores significantly even after controlling for Weber fraction (Table 2). Because $\tilde{\theta}_i$ is computed from response times where higher values indicate slower performance, it enters with a negative coefficient. When both Weber fraction and $\tilde{\theta}_i$ are included without accuracy controls (column 3), both remain significant. However, once overall accuracy (Share Correct) is added (columns 4-6), Weber fraction shrinks to approximately -11 and becomes non-significant, while $\tilde{\theta}_i$ remains highly significant. This pattern demonstrates that Weber fraction largely proxies for overall accuracy once peer-relative ability is accounted for, whereas $\tilde{\theta}_i$ captures variance orthogonal to both static measures.

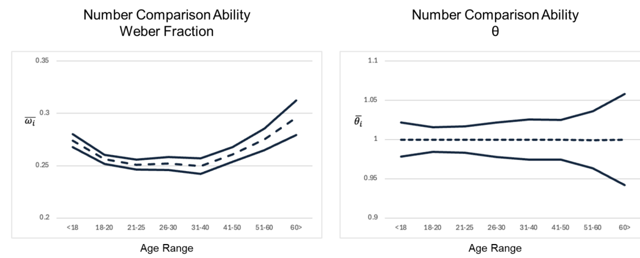

Figure 4: Weber fraction (left) and peer-relative ability (right) across age groups in the adult dataset. Left panel shows traditional static ability measure (accuracy across difficulty levels); right panel shows our adaptation-adjusted measure ($\tilde{\theta}_i$, see Methods). Error bands are 95% CI. Peer-relative ability is normalized to 1 within cohorts by construction, with increased variance at older ages.

The relationship between within-session dynamics and achievement shows domain specificity (Figure 5): adaptation trends predict math scores strongly, science scores moderately, and writing scores negligibly. This specificity indicates that adaptation in numerosity tasks captures optimization relevant to mathematical reasoning rather than general cognitive efficiency.

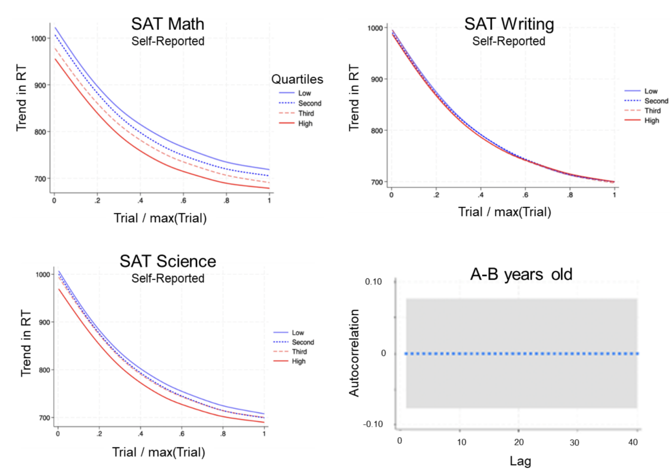

Figure 5: Domain specificity of adaptation-achievement relationship. Top panels show within-session trajectories (RT trends) by SAT score quartile for math, science, and writing. Bottom left shows residual autocorrelation function for 20-25 age bracket (grey area: 95% CI); near-zero autocorrelation at all lags confirms that extracted trends capture all systematic within-session dynamics. Pattern is consistent across all age groups.

Table 1: Within-session adaptation trends by math achievement group (children, 4th and 6th grade). Controls for individual and trial fixed effects. Children with above-median math scores show systematically different adaptation patterns across all performance metrics.

	RT Trend	Share Correct Trend	Mov. Time Trend	Velocity Trend	AUC Trend
Female	-78.164***	0.073***	588.273***	0.808***	1,548.80***
4th grades	-44.355***	0.174***	220.527***	-0.047*	677.446***
Above Median Math Score	50.991***	0.142***	144.864***	-0.088***	641.977***
Above Median Weber Ratio	-136.227**	0.012**	51.182	0.441***	-312.063***
Constant	863.392***	0.405***	298.222***	1.231***	1,190.07***
Observations	26,721	26,721	26,721	26,721	26,721
R-squared	0.881	0.877	0.729	0.889	0.730

*** p<0.01, ** p<0.05, * p<0.1. AUC: Area under the curve.

Table 2: Math achievement regressions (adults). Peer-relative ability $\tilde{\theta}_i$ predicts SAT math scores beyond Weber fraction. Once accuracy is controlled (columns 4-6), Weber fraction loses explanatory power while $\tilde{\theta}_i$ remains significant.

	(1)	(2)	(3)	(4)	(5)	(6)
Peer-relative ability ($\tilde{\theta}_i$)		-6.052***	-8.264***	-8.116***	-7.472***	-6.029***
Weber Fraction	-64.061***		-67.578***	-11.033	-11.792	-11.595
Share Correct				93.459***	74.243***	46.568***
Constant	85.026***	74.338***	94.208***	7.720	38.442**	7.991
Observations	10,548	10,548	10,548	10,548	10,548	10,548
R-squared	0.035	0.004	0.042	0.045	0.155	0.456

Controls: age, gender, education, mean response times. *** p<0.01, ** p<0.05, * p<0.1

Peer-relative ability and Weber fraction are independent dimensions

Peer-relative ability $\tilde{\theta}_i$ and Weber fraction are essentially uncorrelated ($r \approx 0.02$; Figure 2), confirming that they capture distinct aspects of cognitive performance. This independence demonstrates that adaptation-adjusted ability measures provide unique information about individual differences that traditional static measures do not capture. The Weber fraction measures perceptual precision averaged across trials; $\tilde{\theta}_i$ measures stable processing capacity after factoring out cohort-level within-session optimization dynamics.

Discussion

Cognitive assessment often treats sequential task performance as noise around stable traits. Our results show that this assumption is frequently violated: even in simple tasks with fixed rules and randomized difficulty, performance exhibits structured within-session dynamics. Traditional static summaries can therefore conflate stable processing capacity with real-time optimization, biasing inferences about individual differences. This conflation is not specific to mathematical cognition. It threatens the validity of behavioral assessments across psychology, neuroscience, and behavioral economics wherever performance is measured sequentially.

Across two datasets (10,000+ adults; 243 children), within-session dynamics are systematically related to math achievement beyond static ability proxies. Using a transparent normalization that defines a cohort-level adaptation trajectory, we construct a peer-relative performance index $\tilde{\theta}_i$. In adults, once overall accuracy is controlled, Weber fraction contributes little additional explanatory power, whereas $\tilde{\theta}_i$ remains predictive. This pattern is consistent with Weber fraction reflecting a mixture of perceptual precision and within-session optimization.

The evidence for this interpretation is threefold. First, adaptation trends emerge even in tasks requiring minimal rule learning (dot comparison), suggesting these trends reflect within-session adjustment rather than extended rule acquisition. Second, residuals after removing adaptation trajectories exhibit near-zero autocorrelation, suggesting that systematic temporal structure resides in the smooth trends we extract rather than in unmodeled dependencies. Third, adaptation dynamics vary systematically by math achievement across multiple performance metrics (response times, accuracy, movement kinematics), establishing them as genuine cognitive signals rather than measurement artifacts.

These findings reframe the debate on whether perceptual processing underpins symbolic reasoning (Bugden et al., 2021; Deary, 1994; Price et al., 2012). We hypothesize that the link between non-symbolic numerosity discrimination and formal math achievement does not rest solely on perceptual precision, but on the efficiency with which individuals adapt cognitive compression strategies under working memory constraints. When participants optimize performance across trials in simple dot comparison tasks, they may reveal their capacity for dynamic recalibration of cognitive control parameters. This capacity would predict success in complex symbolic mathematics where similar optimization under cognitive constraints is required.

Our peer-relative ability estimates exhibit systematic developmental patterns. While normalized to unity within cohorts by construction, variance increases with age (Figure 4), echoing known patterns of cognitive heterogeneity in older adults (Hartshorne & Germine, 2015). This increased variance may reflect accumulated differences in strategy selection, motivational engagement, or neurochemical regulation of cognitive control. That adaptation dynamics show age-related variance structure positions them as a candidate cognitive phenotype worthy of investigation beyond mathematical cognition.

The mechanisms underlying within-session adaptation remain incompletely specified. Our framework treats adaptation trajectories as smooth deterministic trends that scale with individual ability, but does not specify whether optimization operates through attention allocation, confidence calibration, motor preparation, or strategy adjustment. Process models such as the drift-diffusion model (Ratcliff et al., 2016) typically hold parameters (drift rate, boundary separation) constant across trials. Our results suggest these parameters evolve systematically during task performance. Incorporating dynamic parameter adjustment into process models may reveal how cognitive traits manifest through real-time optimization rather than static capacity alone.

The broader implication is methodological. Sequential tasks induce behavioral dynamics that are not noise to be averaged away. They are systematic signals of how individuals optimize performance under cognitive constraints. Models that treat trial-by-trial variation as measurement error around a stable trait do not capture this signal. Cognitive inference requires accounting for temporal structure in performance. The cost of ignoring within-session dynamics is not merely reduced statistical power. It is fundamentally biased characterization of individual differences.

Adaptability is not peripheral to cognition. It is central to how competence expresses itself in real time. Capturing this temporal structure is essential for accurate inference about cognitive capacity. Our framework provides a tractable approach for normalizing the ability-adaptation non-identification in sequential tasks under a transparent normalization, yielding a peer-relative ability index and cohort-level within-session trajectory. The method is simple, requires no parametric assumptions about adaptation trajectories, and generalizes across performance metrics. Models that incorporate rather than ignore within-session dynamics will yield more accurate characterizations of how minds adapt, optimize, and express capability over time.

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