Toward a Mechanistic Account of Cognitive Inhibition: Integrating Computational Modeling and Psychometrics

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Abstract

Cognitive inhibition is crucial for resolving conflict in decision making, but it is often estimated using reaction time differences between congruent and incongruent trials, which ignores accuracy and conflates inhibition with other processes. To address this, we adapted a Diffusion Model with Inhibition (DMI) to formally quantify cognitive inhibition—the suppression of task-irrelevant information—within a decision-making framework. This approach disentangles inhibition from processing speed and non-decision time. Combining computational modeling with structural equation modeling across multiple conflict tasks, we tested whether inhibition forms a coherent latent factor. Applying the same framework to large-scale data from over 1 million participants in the Implicit Association Task revealed distinct lifespan trajectories of inhibition across adulthood and aging. Overall, our findings show how computational modeling can uncover latent cognitive mechanisms underlying individual differences in inhibition.

Keywords: Cognitive inhibition; computational modelling; conflict tasks; evidence accumulation models.

Introduction

One of the objectives of cognitive science is to understand how people generate adaptive behaviors across a range of contexts. Cognitive inhibition - the ability to suppress task-irrelevant or conflicting information—is an essential component of executive functions that enables people's flexible behaviors (Diamond, 2013). It serves an important role in cognitive development, especially for attention, memory, motor control, and verbal control of behavior (Harnishfeger & Bjorklund, 1993). Despite its theoretical importance, the measurement of inhibition as a coherent cognitive construct has remained elusive.

Over the past two decades, researchers in psychometrics have sought to establish cognitive inhibition as a psychometric construct (Miyake et al., 2000). The key prerequisite for its establishment is to find robust correlations between multiple measures of this construct. However, researchers have repeatedly failed to identify robust, coherent factors for inhibition (Karr et al., 2018; Rey-Mermet et al., 2019; Von Bastian et al., 2020). In many cases, either inhibition tasks did not cluster together (De Simoni & Von Bastian, 2018; Guye & Von Bastian, 2017) or one task dominated the factor structure (Chuderski, 2015; Kane et al., 2016), suggesting task-specific variance rather than a domain-general inhibitory construct. These findings have fueled debates over whether inhibition represents a distinct, measurable ability or merely a statistical artifact of individual tasks.

A major reason for these inconsistencies lies in limitations of traditional behavioral measures. Traditional psychometrics of inhibition usually uses either performance in the incongruent condition (Lee et al., 2013; Van Der Ven et al., 2013) or the difference in average reaction time between the congruent conditions (low inhibition) and incongruent conditions (high inhibition) in conflict tasks (Bender et al., 2016; Friedman & Miyake, 2004).

The problem with this approach is that there is much trial-by-trial variability in RTs, adding measurement noise to the mean RT that is unaccounted for (Rouder & Haaf, 2019). These measures also neglect accuracy information (Yangüez et al., 2024), which can lead to misleading conclusions if participants adopt different speed-accuracy trade-off settings (see Heitz, 2014, for a review).

Moreover, these measures also conflate multiple processes, including stimulus encoding, evidence accumulation, and motor execution, thereby obscuring the specific contribution of inhibitory control. As a result, the observed RT differences between congruent and incongruent conditions can arise from several underlying mechanisms, making it impossible to isolate inhibition from other cognitive components.

To overcome these methodological limitations, recent research in cognitive psychometrics has advocated the use of process models—formal computational models that link observed behavior to latent cognitive mechanisms (Batchelder, 1998; Vandekerckhove, 2014). Among these, the Drift Diffusion Model (DDM) has proven particularly successful across a range of paradigms, tasks, and conditions (Donkin & Brown, 2018; Evans & Wagenmakers, 2020; Ratcliff et al., 2016). It has been experimentally validated through multiple experiments (Arnold et al., 2015; Lerche & Voss, 2019; Voss et al., 2004) and has been used to quantify individual differences in cognitive traits such as mental speed and caution (Ratcliff, 2008; Von Krause et al., 2022).

There are some attempts that applied DDM to conflict tasks and most of the time drift rates were used as the relevant parameter to measure inhibition (Löffler et al., 2024; Yangüez et al., 2024). As a result, inhibition estimates

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derived from drift rate are contaminated by general processing speed, precluding the identification of a distinct inhibitory mechanism (Löffler et al., 2024). Indeed, Löffler used a DDM-based analysis and could identify processing speed as a factor, but failed to identify a distinct factor of attentional control as a distinct. It is plausible that this result arises from the lack of an explicit inhibitory mechanism in the DDM.

Other attempts to model inhibition involve more complex assumptions than the DDM. For example, the diffusion model for conflict tasks (Ulrich et al., 2015) has been applied to different datasets, including Stroop-like tasks (Hedge et al., 2022). Despite observing relatively strong correlations between parameters capturing non-conflict processing (drift rate and boundary separation), the parameters reflecting attentional control were only weakly correlated across tasks. There are several existing alternative accounts of conflict tasks, for example, the Dual-Stage Two-Phase model (DSTP) model (Hübner et al., 2010) and Shrinking Spotlight (SSP) model (White et al., 2011). However, such models are also very specifically designed for particular conflict tasks, while we hope to measure inhibition more generally.

The purpose of this study is to establish cognitive inhibition as a coherent latent construct grounded in computational mechanisms. By integrating computational modeling, simulation-based Bayesian inference, and structural equation modeling (SEM), we estimate model-based inhibition parameters from behavioral datasets containing multiple conflict tasks and a large-scale dataset using the Implicit Association Test (IAT). This paper addresses three central questions: (1) whether the inhibition model we will now propose reliably reproduces empirical reaction time and accuracy patterns; (2) whether inhibition parameters converge on a common latent factor across tasks (convergent validity); and (3) how model-based inhibition changes across the lifespan (external validity). Together, these analyses bridge computational modeling and psychometrics, advancing a mechanistic framework for understanding inhibition as a latent cognitive construct.

Method

Computational Framework

We propose the Diffusion Model with Inhibition (DMI) as a measurement model for inhibition that explicitly represents the interaction between multiple evidence streams. The model comprises four accumulators (Accumulators 1-4 in Fig. 1A) encode evidence for two alternative responses (I_1, I_2). In applying the DMI to standard conflict tasks, we adopt the widely used dual-route assumption (De Jong et al., 1994; Ulrich et al., 2015), positing a controlled process (C) and an automatic process (A), as shown in Fig. 1A.

The controlled process accumulates task-relevant evidence (x_1) as the difference between accumulator 1 and 2, whereas the automatic process accumulates task-irrelevant evidence (x_2) as the difference between accumulator 3 and 4. Their dynamics are governed by the stochastic differential equations:

$$dx_1 = v_1 dt + \sigma\, dW_{1,t}$$
$$dx_2 = (mv_1 + kx_1)dt + \sigma\, dW_{2,t}$$

Here, v_1 denotes the drift rate of the controlled process and mv_1 the drift of the automatic process, scaled by $m \in (0, 1)$. The parameter k quantifies unidirectional, top-down inhibition from the controlled to the automatic process; no inhibition operates in the reverse direction. This formulation can be interpreted as a dynamic control mechanism, whereby top-down control exerts stronger suppression as task-relevant evidence accumulates. This is broadly consistent with views of inhibition as emerging during conflict resolution rather than reflecting a fixed resource. Both processes are driven by independent Gaussian noise ($dW_{1,t}$, $dW_{2,t}$). To prevent the inhibitory interaction from becoming excitatory, the inhibition term is set to zero when x_1 and x_2 are both positive or both negative.

The DMI differs from classical accumulator models in that decisions are based on a superimposed decision variable, formed by summing the two diffusion processes. A response is generated when this combined process first reaches either boundary a or $-a$, and the observed reaction time (RT) equals this first-passage time plus non-decision time (NDT).

This architecture captures the key dynamics of conflict tasks (Fig. 1B and Fig. 1C). In congruent trials, both accumulators drift in the same direction towards the correct response, statically facilitating correct responses as the controlled and automatic processes act consistently. In incongruent trials, the automatic process reverses direction, opposing the controlled process and slowing accumulation, thereby increasing response times and error rates. In this way, the DMI provides a mechanistic account of cognitive inhibition expressed as slower responses under conflict.

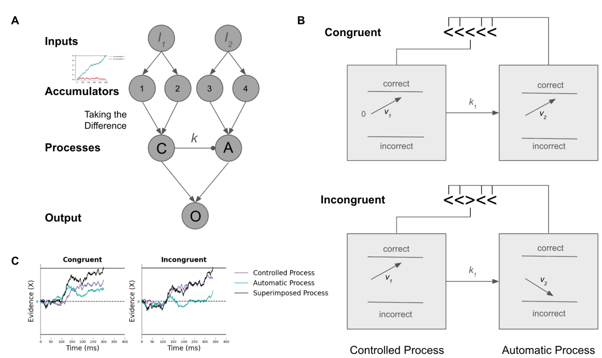

Figure 1: **A**) Schematic illustration of the DMI. **B**) Mechanism of DMI in conflict tasks (i.e. Flanker Task). **C**) Simulated trajectories from one trial for the controlled process (purple), the automatic process (blue), and the superimposed process (black) in the congruent condition (left) and incongruent condition (right).

Model Fitting Because the likelihood of the DMI is analytically intractable, we employed amortized simulation-based inference (BayesFlow) to learn an approximate posterior directly from simulated data (Radev et al., 2020). It is a simulation-based framework that uses neural networks to approximate posterior distributions, which allows efficient estimation of analytically intractable and computationally demanding decision-making models. BayesFlow consists of a summary network and an inference network jointly trained on synthetic data from the full model, enabling fast and accurate inference on new data. This approach greatly reduces computational cost while preserving inference quality, ensuring transparent, robust, and scalable estimation of cognitive models.

The summary network was specified as a SetTransformer with a 128-dimensional latent representation and two multilayer perceptron (MLP) blocks of depth 5 each. The inference network employed a conditional normalizing flow (FlowMatching) with six residual blocks, each consisting of 256 hidden units. These components were combined to learn the posterior distribution over model parameters. Training was conducted for 150 epochs with 500 batches per epoch and a batch size of 16. We used the Adam optimizer with gradient clipping (clipnorm = 1.0) and a cosine decay learning rate schedule starting at 5×10^{-4} and annealing to 10^{-6} over the course of training.

Parameter Recovery To assess whether the proposed model and inference procedure could reliably recover the underlying parameters, we conducted a parameter-recovery analysis using simulated data. Parameters were sampled from the same prior distributions used during model training, and synthetic datasets were generated by forward simulation of the model under the same experimental design as the empirical data with a sample size of 300. The trained inference network was then applied to these simulated datasets to obtain posterior estimates for each parameter. Recovery was evaluated by comparing true parameter values with posterior summaries (mean ± standard deviation) across 200 simulations, using both visual inspection and Pearson correlations between true and estimated parameters.

Parameter recovery was generally strong across most model parameters (see Fig. 2). Drift rate (*v*), decision threshold (*a*), and non-decision time (*NDT*) exhibited near-perfect recovery, with posterior estimates closely aligned with true values and correlations approaching unity. The scaling parameter (*m*) was recovered with moderate accuracy, showing greater variability around the identity line. Recovery for the inhibition parameter (*k*) was weaker than the other parameters, with substantial dispersion and reduced correspondence between true and estimated values. Such a result is expected, given how notoriously difficult it is to estimate inhibition parameters in evidence-accumulation models. For example, inhibition in the Leaky Competing Accumulator model, which also assumes leakage within accumulators is practically non-identifiable (Miletić et al., 2017; Usher & McClelland, 2001). The key result here is that the inhibition dynamics are recoverable at all. However, it would be prudent for researchers using the model to perform situation-specific recovery simulations to check whether the inhibition parameter is going to be neatly recovered.

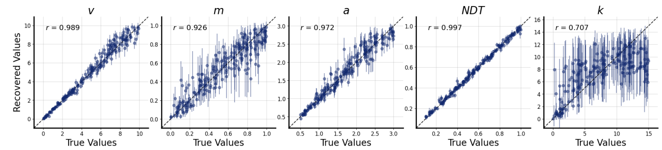

Figure 2: Recovery of DMI parameters from simulated data. Each panel shows the relationship between true parameter values (x-axis) and posterior mean estimates obtained from the trained inference network (y-axis) for drift rate of the controlled process (*v*), scaling parameter (*m*), decision threshold (*a*), non-decision time (*NDT*), and inhibition (*k*). Points represent individual simulations, with error bars indicating posterior standard deviations. The dashed diagonal denotes perfect recovery. Pearson correlation coefficients (*r*) are reported in each panel.

Datasets

Cognitive Control dataset We used a dataset from a reanalysis of data originally published by Rey-Mermet (et al., 2018), comprising the full sample and eight cognitive control tasks: color Stroop, number Stroop, arrow flanker, letter flanker, Simon, global–local, positive compatibility, and negative compatibility tasks. Prior to reanalysis, participants were excluded if they failed to meet the original psychiatric or demographic inclusion criteria or if their accuracy fell below .70 in any task. The number of trials per task ranged from 100 to 300. After filtering, 190 participants with complete data across all eight tasks remained.

Implicit Attitude Task from Project implicit The Race IAT (Xu et al., 2014) is a cognitive test that requires participants to sort words (e.g., 'good' and 'bad'), and images (e.g., of a Black or White person) into two categories using specific keys. The key pairings change partway through the experiment (e.g., 'good' is first paired with an image of a Black person, and then with one of a White person), resulting in so-called congruent and incongruent conditions. While the difference in reaction speed between these pairings is typically used to measure implicit bias, this study used the IAT only as a standard example of a simple, two-choice conflict task, not to measure bias. Here, we use it to measure inhibition because it provides a large-scale task with a well-defined congruent–incongruent structure, allowing reliable estimation of evidence accumulation dynamics across conditions. Reaction times faster than 0.2s or slower than 4s were excluded from modeling.

We included participants ranging from approximately 10 to 80 years of age, with uneven sampling across age bins. Early adulthood was most densely sampled, with roughly 180,000–400,000 participants per bin between ages 20 and 40, followed by a gradual decline across middle adulthood (approximately 135,000–185,000 per bin between ages 40 and 60). Older age ranges were more sparsely represented,

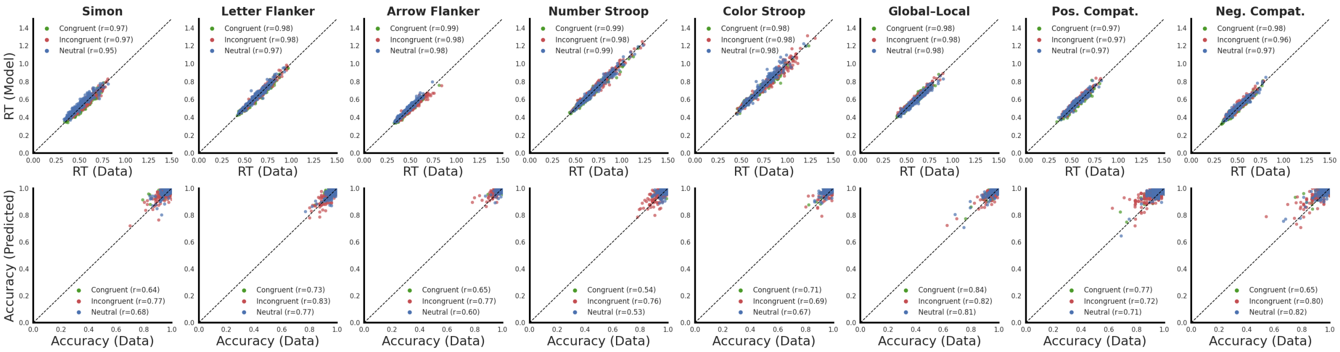

Figure 3: Model predictions for the eight tasks from Rey-Mermet (et al., 2018). The first row shows reaction times and the second row shows accuracies. Each panel displays participant-level data, a dashed diagonal line indicating perfect correspondence between model predictions and observed data, and an inset reporting the Pearson correlation, which is high in all subplots.

with about 95,000 participants aged 60–70 and approximately 40,000 aged 70–80.

SEM

We used structural equation modeling (SEM) to examine the latent structure of task-based parameters via confirmatory factor analysis (CFA) with maximum likelihood estimation and robust (Huber–White) standard errors. All variables were standardized, and latent factor variances were fixed to 1 for identification. Model fit was evaluated using χ^2, CFI, SRMR, and RMSEA, following established cutoffs (Hu & Bentler, 1999). Models also had to meet substantive criteria, including adequate factorability (KMO > .60), meaningful factor loadings (mostly > .30), reasonable error variances (< .90), absence of single-indicator dominance, and sufficient shared variance across tasks. Factor reliability was assessed using McDonald's ω, with values around .70 indicating acceptable reliability.

Curve Fitting

For the IAT task, we used linear Bayesian ridge regression to characterize age-related trends in model parameters. Age was entered as a continuous predictor, and regression coefficients were estimated using a Bayesian ridge framework, which places Gaussian priors on regression weights and performs automatic L^2 regularization to mitigate overfitting and multicollinearity. Models were fit separately for each parameter using maximum a posteriori estimation as implemented in scikit-learn (Pedregosa et al., 2012). Prior hyperparameters were set to weakly informative values, and all models were evaluated using out-of-sample performance metrics.

Results

Inhibition can be extracted as a common factor

Model Fits Figure 3 shows eight scatterplots comparing model predictions generated from MAP parameter estimates of the DMI with empirical data across three conditions—Congruent, Incongruent, and Neutral. The top row shows predicted versus observed mean reaction times, while the bottom row shows predicted versus observed accuracies. Overall, the results demonstrate an acceptable fit between the model and the empirical data across all conditions, indicating that the model successfully captures both reaction time and accuracy patterns.

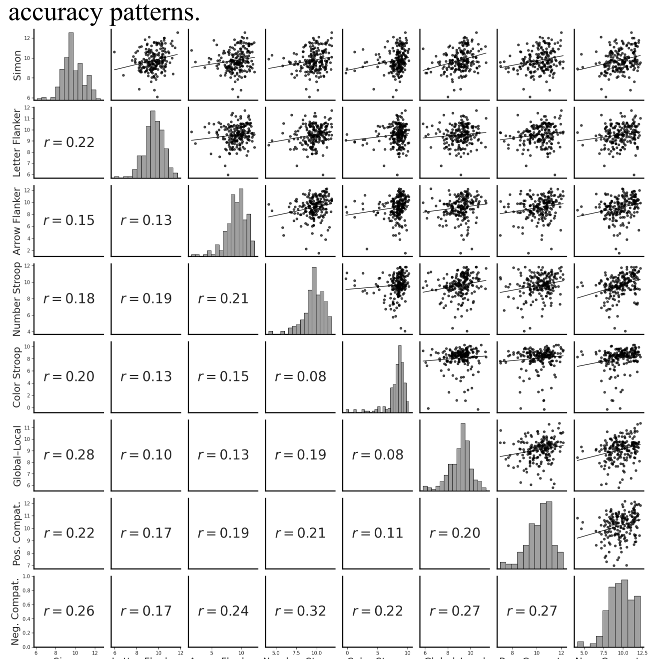

Figure 4: Pairwise correlation between estimated inhibition from the eight tasks in Rey-Mermet (et al., 2018). Dots represent participants. The plots reveal moderate to strong positive correlations between tasks, suggesting systematic covariation in their estimates, while others show weak or no clear relationship.

Cross-task Correlations Figure 4 shows a pairwise correlation matrix illustrating the relationships among estimated top-down inhibition across the eight datasets. Each off-diagonal panel displays scatterplots with fitted regression lines and shaded confidence intervals, while the diagonal panels show histograms of individual parameter distributions. Overall, the figure provides a compact visualization of the dependencies and distributions among model parameters, highlighting both linear associations and variability across estimates.

Single-Factor Confirmatory Factor Analysis (CFA) In the next step, we aimed to find a coherent factor of inhibition control. To this end, we fitted a model in which the top-down inhibition parameter estimated from all tasks loaded on a single factor. By linking inhibition parameters across tasks within a CFA, we test whether inhibition behaves as a coherent latent construct rather than task-specific variance.

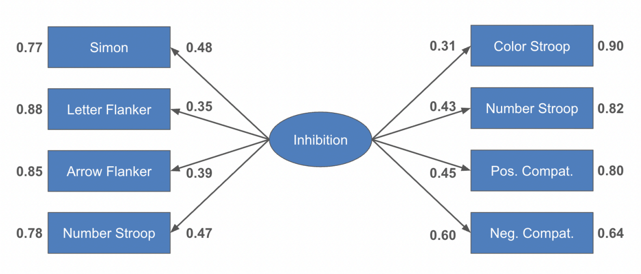

Figure 5: One-factor confirmatory factor analysis (CFA) of inhibition. Observed task measures (rectangles) load onto a single latent inhibition factor (ellipse). Numbers on the arrows indicate standardized factor loadings, and numbers next to each indicator represent standardized residual variances. All loadings are positive and statistically significant, but vary in magnitude, indicating moderate shared variance alongside substantial task-specific variance (i.e., task impurity).

The one-factor confirmatory factor analysis showed excellent fit to the data, $\chi^2(20) = 10.11$, $p = .97$. Incremental fit indices indicated excellent fit (CFI = 1.00, TLI = 1.13). Absolute fit indices were also strong, with RMSEA = .00, 90% CI [.00, .01]. All indicators loaded significantly on the latent inhibition factor (standardized loadings λ = .31–.60), though loadings were generally modest, suggesting substantial task-specific variance (Figure 5). Model-based factor reliability, assessed using McDonald's ω, was moderate ($\omega = .64$), indicating a limited but nontrivial amount of shared variance across inhibition tasks. Sampling adequacy was evaluated using the Kaiser–Meyer–Olkin (KMO) measure, which indicated good overall adequacy (KMO = .78), with item-level MSAs ranging from .75 to .82. Together, these results suggest that while a common inhibition factor can be identified, its measurement is characterized by moderate reliability and considerable task impurity.

Lifespan trends of inhibition

To examine age-related nonlinearities in model parameters, we fit piecewise linear Bayesian ridge regressions allowing up to two change points in age (Figure 6). Model selection was based on adjusted R^2 evaluated on a held-out validation set, and the selected models were subsequently refit to the full dataset for visualization and summary statistics.

Overall, allowing age-related change points modestly improved model fit for several parameters, although effect sizes were small (validation adjusted R^2 ranging from 0.006 to 0.092). Importantly, the location and number of selected change points varied across parameters, indicating heterogeneous age trajectories rather than a single global transition.

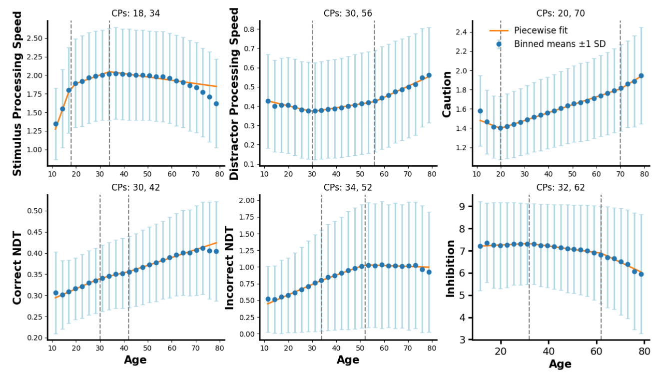

Figure 6: Age-related changes in DMI parameters based on 1 million participants. Binned means (points) and fitted piecewise functions (lines) are shown for each parameter as a function of age. Error bars denote ±1 SD, and vertical dashed lines indicate estimated change points.

Stimulus Processing Speed The drift rate for stimulus information serves as a proxy to measure general mental speed of the controlled process. It showed two change points at approximately ages 18 and 34. Drift rate increased rapidly from adolescence into early adulthood, reached a plateau through mid-adulthood, and then declined gradually at older ages, indicating an early developmental increase followed by age-related slowing later in life.

Distractor Processing Speed The scaling parameter for the automatic process represents the relative amplitude compared to the drift rate of the control process. It exhibited change points around ages 30 and 56. This parameter followed a shallow U-shaped trajectory, with a slight decrease from adolescence into early adulthood followed by a gradual increase in later adulthood. The late-life increase may be particularly informative in light of general age-related slowing, as it could reflect mechanisms contributing to slower RTs in older adults, whereby evidence accumulation is increasingly influenced—or dragged—by task-irrelevant information.

Caution The decision threshold parameter provides an estimate of response caution. It showed change points near ages 20 and 70. Threshold values decreased from adolescence into early adulthood and then increased steadily across the adult lifespan, consistent with progressively more cautious decision-making with age.

Correct NDT The non-decision time for correct responses exhibited change points at approximately ages 30 and 42 and increased monotonically with age, with a somewhat steeper increase from early adulthood onward. This contrasts with Von Krause et al. (2022), who carried out a similar analysis with the DDM (i.e., without inhibition) and reported a decrease between ages 10 and 15.

Incorrect NDT The non-decision time for incorrect responses showed change points near ages 34 and 52, increasing through midlife before plateauing or slightly declining at older ages. The change-point model misses the minor decrease that starting at age 75.

Inhibition Cognitive inhibition refers to the ability to suppress task-irrelevant information. In the present model it is the suppression of the automatic process by the controlled process. The inhibition parameter showed change points around ages 32 and 62. Inhibition strength shows a slight increase from adolescence through mid-adulthood, followed by a modest decline and then a more pronounced decrease in later adulthood. Together with changes in processing speed, reduced inhibition provides a plausible source of slower response times in incongruent conditions, as weaker inhibition allows the automatic process to exert greater influence on the superimposed evidence accumulation.

Across all parameters, the fitted piecewise functions closely tracked the binned empirical means, capturing gradual nonlinear age-related changes rather than abrupt discontinuities. Moreover, most parameter trajectories were broadly consistent with diffusion model results reported by Von Krause et al. (2022). Together, these results suggest that age-related changes in decision-making parameters are parameter-specific and largely continuous, with piecewise change points serving primarily as descriptive approximations of smooth developmental and aging-related trajectories. Importantly, the inhibition parameter shows comparatively weaker but meaningful recovery and exhibits a theoretically sensible pattern across the lifespan.

Conclusion

The purpose of the present study was to establish a coherent factor of cognitive inhibition from other cognitive processes. Using the DMI, we isolated an inhibition parameter that quantifies the degree to which competing information sources interact with each other during decision making in the conflict tasks. This model-based approach captures a process that can be interpreted as inhibition, while disentangling it from related constructs such as processing speed, response caution, and non-decision.

Our results have provided consistent evidence for the potential validity of this computational approach. First, the DMI demonstrated a good ability to reproduce key empirical RT and accuracy patterns across multiple tasks that requires cognitive inhibition. In addition to capturing the central tendencies of the data, the model also has relatively good sensitivity in parameter recovery, confirming its reliability to reflect core properties of human decision behavior.

The cross-task correlations of the estimated inhibition parameters revealed systematic covariation across datasets from Rey-Mermet et al. (2018), indicating that inhibition operates as a stable individual difference rather than a task-specific property. Single-factor CFA further supported this interpretation: inhibition parameters from diverse tasks loaded significantly and evenly onto a single latent factor. This finding contrasts with previous psychometric studies relying on raw RT or accuracy measures, which failed to identify a coherent inhibition factor. By grounding the latent construct in a computational mechanism, the present work provides a theoretically interpretable foundation for studying individual differences in inhibitory control.

Lifespan analyses using a large-scale IAT dataset (Xu et al., 2014) from over 1 million participants revealed a clear developmental trajectory of top-down inhibition: slightly increasing from adolescence to early adulthood, modest decline during midlife, and decrease from late middle age onward. This trajectory is consistent with well-established patterns in cognitive control and executive function (Ferguson et al., 2021; Idowu & Szameitat, 2023), suggesting that the inhibition parameter derived from the DMI has good external validity and captures genuine psychological variance rather than measurement noise. Other model parameters, such as drift rate and non-decision time, showed age-related trends consistent with prior diffusion-model analyses (Von Krause et al., 2022), further validating the robustness of our approach.

The present formulation assumes state-dependent, unidirectional inhibition from the controlled to the automatic process. While this provides a parsimonious implementation, alternative parameterizations—such as constant inhibition or bidirectional interactions between processes—may capture different aspects of cognitive control. Exploring these alternatives may help clarify whether the observed effects are specific to this formulation or reflect a more general property of inhibitory mechanisms.

A further limitation concerns the use of point estimates (MAP) from the posterior distributions in CFA. While this approach simplifies estimation, it ignores uncertainty in individual parameter estimates and may lead to underestimation of measurement error and overconfidence in factor loadings. In principle, propagating full posterior uncertainty into the SEM—e.g., via hierarchical modeling or multiple imputation—would provide a more accurate characterization of latent structure. Future work should explore approaches that integrate posterior uncertainty more fully into the psychometric analysis.

This work demonstrates the power of combining simulation-based inference with cognitive psychometrics to identify a coherent, mechanistically grounded latent factor of cognitive inhibition. Using amortized Bayesian inference, the DMI serves as a process-based measurement framework linking theory to behavior through interpretable parameters. Integrating the model with SEM bridges cognitive theory and psychometric representation. More broadly, this study contributes to the development of cognitive psychometrics, where process models define and measure latent constructs. By formalizing inhibition as a latent parameter within a generative model, we move beyond descriptive test scores toward mechanistic explanations of individual differences.

Acknowledgments

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