Attentional Inertia and Residue in Dual-Tasking Performance: Examining Within- and Between-Task Variability Using Multilevel Vector Autoregression Models

Rinseo Park (rinseo@stanford.edu)[1], Christoph Naefgen[2], Robert Gaschler[2], & Nilam Ram[1,3]
[1]Department of Communication, Stanford University
[2]Department of Psychology, FernUniversität in Hagen
[3]Department of Psychology, Stanford University

Abstract

When individuals attempt to complete multiple tasks simultaneously, constraints on how attention is deployed influence performance. However, experimental findings from dual-tasking paradigms often rely on analysis of aggregated data that obscure study of how the carryover or spillover of attention over time – attentional inertia and residue – changes within person and over time. This study introduces an analytical framework for examining if and how attentional control settings from an initial task persist both within the same task (attentional inertia) and between two different tasks (attentional residue) across trial, session, and person levels. Leveraging reaction time data from 58 participants who completed 20 online sessions of dual-task performance blocks, we employed multilevel vector autoregression models to simultaneously model the lagged and cross-lagged effects. Our results demonstrate that both positive inertia and positive residue effects manifest and that they are positively correlated, especially for those originating from the same initial task.

Keywords: attention; dual-tasking; attentional inertia; attentional residue; multilevel analysis; dyadic analysis

Introduction

In everyday life, individuals engage and frequently switch among multiple tasks. Studies suggest that when the mental resources involved overlap, the processes governing allocation and reconfiguration of resources across tasks interfere with each other (Monsell, 2003). The "interference" manifests in multiple ways. For example, when individuals attempt to complete two tasks simultaneously, performance of a given task might interfere with subsequent performances of both the same task – which is often referred to as *attentional inertia* – and the other task – *attentional residue*. Although both types of interference have been documented in task switching and sustained attention literatures, studying them in a dual-tasking scenario may require multivariate models that accommodate both within- and between-task relations and the multilevel structure of repeated measures nested within individuals. Departing from traditional between-subjects configuration of experimental designs and analysis of session-level aggregate data (Hamaker, 2012; Molenaar, 2004) we introduce the possibility of using multilevel vector autoregression (mlVAR) models to examine the within- and between-task variability in dual-tasking performance across trials, sessions, and persons.

Attentional Inertia and Residue

In the task switching literature, attentional inertia and residue represent two ways that interference between tasks manifests across time. We use and extend these constructs to examine the temporal dynamics in a dual-tasking paradigm where participants perform two tasks simultaneously. Attentional inertia is a carryover effect within the same task (Longman et al., 2014; Richards & Anderson, 2004); for example, when a slower performance on one trial carries forward to the next trial so that it is also slower than expected. Attentional residue is a spillover effect between two different tasks (Leroy, 2009); for example, when a slower performance on one task carries forward to the other task so that it is also slower than expected. Prior research has shown how these phenomena are driven by attentional control settings that influence the allocation of attention and thus performance in a task (Folk et al., 1992; Kaptein et al., 1995; Rossi & Paradiso, 1995). These settings become increasingly persistent when a participant invests more time or cognitive effort into an initial task (Leber & Egeth, 2006; Thompson et al., 2015). Their persistence can also influence performance of other tasks. Wendt et al. (2017) showed that even limited exposure to an initial task can result in the persistence of these settings to a second task. This type of interference manifests as "switch costs," for example when performance declines (increased reaction time or error rates) when shifting between mental sets (Allport et al., 1994; Rogers & Monsell, 1995).

Theoretical Mechanisms of Dual-Task Interference

Interference in the dual-tasking setting is typically measured as the difference in secondary-task reaction times (STRTs) between an experimental condition when two stimuli appear simultaneously and a condition when only one stimulus is presented. The increase in STRTs in the dual-task condition is commonly referred to as the psychological refractory period (PRP) effect and theorized in two frameworks (Klapp et al., 2019; Strobach, 2020). On one hand, bottleneck theory suggests that cognitive processes have a structural bottleneck, characterized by the queuing of cognitive operations and serial processing (Lien et al., 2005; Pashler, 1984, 1994; Telford, 1931; Welford, 1952, 1959). On the other hand, shared capacity theory suggests that cognitive resources are a limited pool, characterized by the sharing of cognitive capacities and parallel processing (Navon & Gopher, 1979; Tombu & Jolicoeur, 2003, 2005).

Regarding the persistence of attentional control settings, these theories provide separate explanations of how the different types of interference – attentional inertia and residue – manifest. Bottleneck theory predicts positive inertia and residue effects, as they both result from structural delay required to reconfigure a single channel (i.e., single channel

In G. Boleda, I. Dautriche, M. Maldonado, C. Saldana and T. Torrent (Eds.), *Proceedings of the 48th Annual Conference of the Cognitive Science Society*

hypothesis). A central processing mechanism governs both carrying over and switching away from an attentional control setting (Allport et al., 1994; Koch et al., 2018; McCann & Johnston, 1992), suggesting positive correlations between lagged and cross-lagged relations originating from an initial task. In contrast, shared capacity theory suggests that attentional inertia and residue effects will be less pronounced or even negative, as multiple processes can operate in parallel, competing for a common resource pool. This theory thus predicts zero to negative correlations among these effects, as a capacity that is used to maintain a setting is no longer available to clear that residue. Previously, Naefgen et al. (2023) found positive correlations between single- and dual-tasking performance at the session and person levels. Similarly, we hypothesize that positive inertia and residue effects manifest and are positively correlated at the trial level, providing further evidence for the bottleneck theory.

Modeling Within- and Between-Task Variability in Attentional Dynamics

Generally, the relations between variables observed in cross-sectional data cannot be used to infer relations between these variables at the person level (Hamaker, 2012; Molenaar, 2004). Thus far, classic findings on switch costs often relied on analysis of (cross-sectional) differences in group-level means (e.g., Allport et al., 1994; Folk et al., 1992; Rogers & Monsell, 1995). In response, there are increasing efforts to introduce multilevel modeling frameworks that support more accurate inference about within-person dynamics (Brose et al., 2012; Wagenmakers et al., 2018). While previous studies on attentional inertia and residue effects have attempted to address how participants' attentional control settings change over time using within-subjects designs and continuous measurements such as eye-tracking data (e.g., Longman et al., 2014; Richards & Anderson, 2004), it is not yet known whether and how the bidirectional attentional effects between two tasks change within person and over time.

We specifically employ multilevel vector autoregression (mlVAR) models that can capture these within-person lagged and cross-lagged relations. mlVARs are increasingly being used to study temporal relations among multiple variables measured on many occasions (Bringmann et al., 2013; Ernst & Haslbeck, 2025). These models have been useful for studying study affect dynamics, including feedback loops among positive and negative emotions and daily stressors (Hamaker et al., 2018; Koval et al., 2012; Kuppens & Verduyn, 2017; Masten & Cicchetti, 2010). These models have also been used to study interpersonal relationships, such as those between parents and children or romantic partners (Bolger & Laurenceau, 2013; Chow et al., 2015; LoBraico et al., 2020). Although these models have not yet been used to study attentional dynamics, similarities in both the general form of the research questions and the longitudinal data structures suggest that they can be useful for study of how attentional inertia and residue manifest in dual-tasking paradigms. Our paper aims to fill this gap.

The Present Study

Our study has three specific aims. First, we propose a trial-level analysis that can better capture the variability in dual-tasking performance. For this aim, we leverage a hierarchical variance decomposition model to partition variance into three levels. Second, we examine how attentional inertia and residue manifest by simultaneously modeling them as the lagged and cross-lagged coefficients in a single framework. Third, we test if and how person-specific inertia and residue parameters are correlated. Following bottleneck theory, we hypothesize that these parameters are positive and positively correlated. For the second and third aims, we use a mlVAR approach that facilitates study of bidirectional influences across two tasks while accommodating the nested structure of multi-trial, multi-session data (repeated trials nested within multiple sessions nested within individuals).

Method

Participants and Procedures

Data were obtained from 58 students at the University of Hagen (12 male, 43 female, 3 not-reporting; age M = 32 years, SD = 8 years, range = 20-53 years) who, during a two-week period, completed at least 20 online testing sessions using their own computers. Comprehensive details about the study can be found in Naefgen et al. (2023), where analysis of session-level RT averages confirmed that better single-taskers were better dual-taskers (i.e., consistency in between-person differences in task performance) and that better single-tasking sessions were also better dual-tasking sessions (i.e., consistency in session-to-session fluctuations in task performance; positive correlations between single- and dual-tasking performance at the session and person levels). In this study, we leverage trial-level RT data from dual-task blocks to examine attentional inertia and residue.

Single/Dual Task At each session, participants completed two single-tasking blocks and a dual-tasking block. In the first block, participants completed 32 trials of Task A. In each trial of this binary decision task, either a "1" or a "2" appeared at the center of the screen and participants were instructed to press the corresponding number key in response. Participants then completed 32 trials of Task B. In each trial of this selection task, an "X" appeared either above, below, left, or right of the center of the screen where a "+" was displayed, and participants were instructed to press the corresponding arrow key. After these first 32 + 32 = 64 single-task trials, participants completed 64 dual-task trials in which the two previous tasks were combined using the left (Task A) and right hands (Task B). The two tasks were performed simultaneously, with instruction that each response be given as soon as it was ready without waiting for the other response. In this dual-tasking block, grouping of responses was alleviated through variation of stimulus onset asynchrony (SOA), where the stimulus onset of Task B was delayed relative to Task A. For each trial, the SOA was randomly selected from 0 ms, 200 ms, 400 ms, 800 ms. In all trials, when the participant made an error, "Error" was displayed on the screen for 300 ms before the next trial. Each task session lasted approximately five minutes. In total, the 58 participants completed between 20 and 33 sessions (*M* = 22, *SD* = 2.53). Data from the dual-task blocks across each participant's first 20 sessions were included in the analysis.

Reaction Time (RT) RTs were recorded for each trial for both Task A and Task B (unit = ms). While all raw RTs were measured from the start of a trial, RTs for Task B in the dual-task blocks were adjusted by subtracting the SOA (from raw RT values) to indicate times relative to stimulus onset.

Stimulus Onset Asynchrony (SOA) The onset of the stimulus for Task B was randomized across trials by a specific amount of SOA = 0 ms, 200 ms, 400 ms, 800 ms. Although neither task was to be preferred to the other, participants responded to Task A before Task B in the majority of trials (~93% of trials). The SOA variable was divided by 1,000 so that one unit corresponds to one second.

Data Preparation

Data preparation proceeded in three stages. First, we recoded RTs for incorrect responses, errors, and outliers as missing data (while leaving the original trial number indices unchanged). Second, we standardized the raw RT data to *z*-scores. Third, we separated the *z*-scores into trial-, session-, and person-level variables to obtain predictors at each level.

Cleaning First, raw dual-task RT data consisted of 73,158 observations across 20 sessions from 58 participants (Task A: *M* = 705, *SD* = 601, range = 7 to 105,388 ms; Task B: *M* = 771, *SD* = 661, range = -754 to 83,888 ms). Prior to analysis, we removed (1) RTs for incorrect responses (*n* = 3,901), (2) RTs that were less than zero, i.e., individual responses that were made before the start of a stimulus (*n* = 38), and (3) outliers that were more than 2,500 ms (*n* = 511). As a result, the final sample consisted of 68,708 observations (93.9% of the raw dataset). Although, outliers were defined as raw RTs > 2,500 ms (highest cutoff used in Ratcliff, 1993), follow-up analyses with different cutoff values and transformations are in supplementary files (available upon request).

Standardization Second, the raw RT data were standardized to *z*-scores to ensure that variances are equal across the two tasks (Chow et al., 2015). To check whether the standardized data conformed to a stationarity assumption, we conducted Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests using trial-level data. These tests indicated that 81% of the RT data for Task A and 89% of the RT data for Task B across all sessions per individual was stationary at the $\alpha = .05$ significance level (Bringmann et al., 2014; Kwiatkowski et al., 1992). We thus proceeded with the stationarity assumption.

Centering Third, to address the three-level nested data structure of dual-tasking blocks, we decomposed the trial-level RT into three variables representing deviations from the sample-, person-, and session-level means (see Bolger & Laurenceau, 2013). The standardized RT for Task A or B at trial *t* for session *s* of person *i*, RT_{ist}, is decomposed such that

$$\mathrm{RT}_{ist} = \mathrm{PersonRT}_{i} + \mathrm{SessionRT}_{is} + \mathrm{TrialRT}_{ist} \quad (0)$$

where person-specific means are denoted by $\mathrm{PersonRT}_{i}$; session-level deviations (from person-specific means) are denoted by $\mathrm{SessionRT}_{is}$; and trial-level deviations (from session-specific means) are denoted by $\mathrm{TrialRT}_{ist}$. For example, a positive value of $\mathrm{TrialRT}_{ist}$ indicates that the RT for trial *t* was longer than the average Task A RT across all 64 trials in session *s* of person *i*. Figure 1 illustrates how this trial-level variability manifests in relation to session- (red/blue dotted lines), person- (red/blue solid lines), and sample-level means (black solid lines at zero).

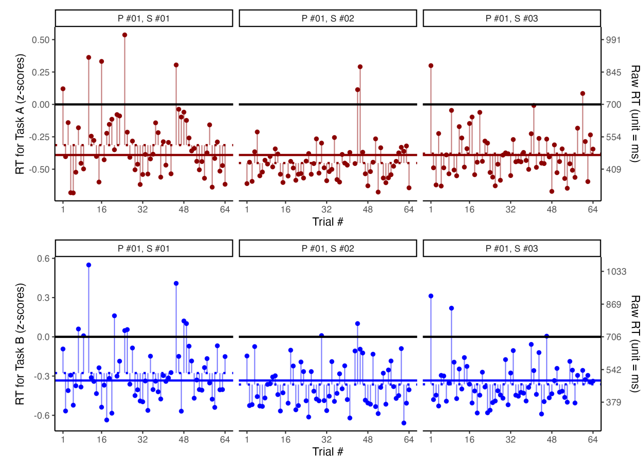

Figure 1: Observed trial-level variability in RT for one participant (P #01) across three sessions (S #01-#03).

Data Analysis

To examine how bidirectional attentional processes manifest at three levels, we employed two modeling approaches: hierarchical variance decomposition and mlVAR models.

Hierarchical Variance Decomposition

To confirm that trial-level analysis can capture the variability resulting from processes of attentional inertia and residue, we fitted unconditional multilevel models to partition variance in the three-level design following set-up in Gatzke-Kopp & Ram (2018). Formally, the standardized RT variables are represented by the combination of trial-level, session-level, and person-level variance, such that

$$\mathrm{RT}_{ist} = \beta_{0is} + \gamma_{00i} + r_{0is} + e_{ist} \quad (1)$$

where e_{ist} is assumed to be distributed as $N(0, \sigma_e^2)$ at the trial level; r_{0is} is assumed to be distributed as $N(0, \sigma_{r0}^2)$ at the session level; and u_{00i} is assumed to be distributed as $N(0, \sigma_{u00}^2)$ at the person level. This approach informs what proportion of the total variance in the observed Task A or Task B RTs may be accounted for by trial-to-trial processes, (including attentional inertia, attentional residue, and noise), as well as the proportions of the total variance that may be accounted for by session-to-session fluctuations and person-to-person differences. The extent of total variance attributed to each level is calculated as $\frac{\sigma^2_{u00}}{\sigma^2_{u00}+\sigma^2_{r0}+\sigma^2_e}$ (person), $\frac{\sigma^2_{r0}}{\sigma^2_{u00}+\sigma^2_{r0}+\sigma^2_e}$ (session), $\frac{\sigma^2_{e}}{\sigma^2_{u00}+\sigma^2_{r0}+\sigma^2_e}$ (trial), where $\sigma^2_{u00} + \sigma^2_{r0} + \sigma^2_e$ equals to the total observed variance in the RT data.

Multilevel Vector Autoregression

To examine how trial-to-trial attentional inertia and residue effects manifest and correlate at the person level, we fitted multilevel VARs that account for both the multivariate (Tasks A and B) and nested (multiple trials within sessions within persons) structure of the data (LoBraico et al., 2020).

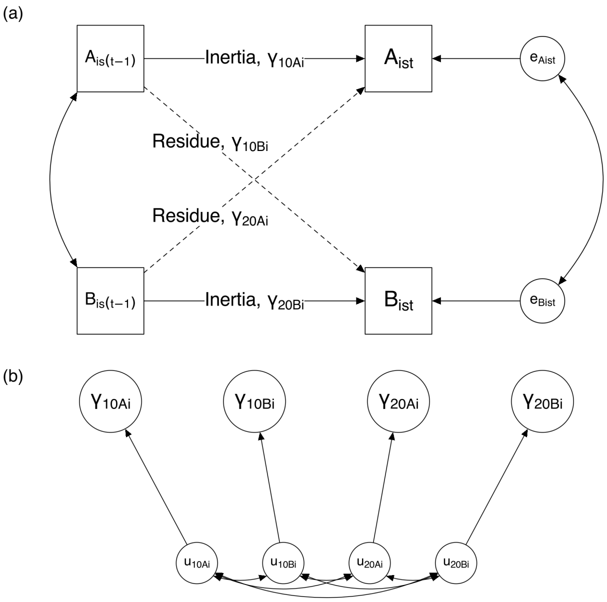

Figure 2: mlVAR model diagram (a) and random effects (b).

As illustrated in the upper panel (a) of Figure 2, attentional inertia and residue effects are modeled as parameters defining autoregressive (inertia, solid arrows) or cross-lagged (residue, dashed arrows) effects across successive trials. Formally,

$$\mathrm{TrialA}_{ist} = \beta_{1Ais}\mathrm{TrialA}_{is(t-1)} + \beta_{2Ais}\mathrm{TrialB}_{is(t-1)} + \beta_{3Ais}\mathrm{SOA}_{ist} + \beta_{4Ais}\mathrm{TrialA}_{is(t-1)}\mathrm{SOA}_{ist} + \beta_{5Ais}\mathrm{TrialB}_{is(t-1)}\mathrm{SOA}_{ist} + e_{Aist} \quad (2.1)$$

$$\mathrm{TrialB}_{ist} = \beta_{1Bis}\mathrm{TrialA}_{is(t-1)} + \beta_{2Bis}\mathrm{TrialB}_{is(t-1)} + \beta_{3Bis}\mathrm{SOA}_{ist} + \beta_{4Bis}\mathrm{TrialA}_{is(t-1)}\mathrm{SOA}_{ist} + \beta_{5Bis}\mathrm{TrialB}_{is(t-1)}\mathrm{SOA}_{ist} + e_{Bist} \quad (2.2)$$

where $\mathrm{TrialA}_{is(t-1)}$ and $\mathrm{TrialB}_{is(t-1)}$ denote the extent of deviation with one time lag at trial (t-1) for session s of person i for Task A and B, respectively. Inertia effects are represented by β_{1Ais} for Task A (A → A) and β_{2Bis} for Task B (B → B), whereas residue effects from Task A to B are represented by β_{1Bis} (A → B) and those from Task B to A are represented by β_{2Ais} (B → A). Next, β_{3Ais} denotes the extent of additional delay in Task A completion associated with SOA and β_{3Bis} in Task B. Additionally, trial-level moderations were included to examine how these effects are moderated by the asynchrony in Task B's stimulus onset. β_{4Ais} denotes the extent of inertia (A → A) effects moderated by SOA, β_{4Bis} denotes the extent of residue (B → A) effects moderated by SOA, β_{5Ais} denotes the extent of residue (A → B) effects moderated by SOA, and β_{5Bis} denotes the extent of inertia (B → B) effects moderated by SOA. e_{Aist} and e_{Bist} are error terms at trial t for session s of person i for Task A and Task B, respectively, which are assumed to be distributed as $N(0, \sigma^2)$ with the correlation parameter ρ. This correlation structure was found to provide the best fit compared to alternatives (i.e., independent, autoregressive).

The session-specific parameters are then simultaneously modeled as a function of person-specific parameters, $\beta_{1Ais} = \gamma_{10Ai} + \gamma_{11Ai}\mathrm{SessionA}_{is} + \gamma_{12Ai}\mathrm{SessionB}_{is}$ (3.1), $\beta_{2Ais} = \gamma_{20Ai} + \gamma_{21Ai}\mathrm{SessionA}_{is} + \gamma_{22Ai}\mathrm{SessionB}_{is}$ (3.2), $\beta_{3Ais} = \gamma_{30Ai} + \gamma_{31Ai}\mathrm{SessionA}_{is} + \gamma_{32Ai}\mathrm{SessionB}_{is}$ (3.3), $\beta_{4Ais} = \gamma_{40Ai}$ (3.4), $\beta_{5Ais} = \gamma_{50Ai}$ (3.5), $\beta_{1Bis} = \gamma_{10Bi} + \gamma_{11Bi}\mathrm{SessionA}_{is} + \gamma_{12Bi}\mathrm{SessionB}_{is}$ (3.6), $\beta_{2Bis} = \gamma_{20Bi} + \gamma_{21Bi}\mathrm{SessionA}_{is} + \gamma_{22Bi}\mathrm{SessionB}_{is}$ (3.7), $\beta_{3Bis} = \gamma_{30Bi} + \gamma_{31Bi}\mathrm{SessionA}_{is} + \gamma_{32Bi}\mathrm{SessionB}_{is}$ (3.8), $\beta_{4Bis} = \gamma_{40Bi}$ (3.9), $\beta_{5Bis} = \gamma_{50Bi}$ (3.10) where, in Eq. 3.1, γ_{10Ai} is the prototypical value of person i's inertia effect for Task A. Positive γ_{11Ai} indicates that session-specific inertia effects β_{1Ais} increase with larger positive session-level deviations. Session-level moderations were included for both Task A (see Eqs. 3.1 to 3.3) and Task B (see Eqs. 3.6 to 3.8).

These person-specific parameters are in turn modeled as a function of sample-level parameters, $\gamma_{10Ai} = \pi_{100A} + \pi_{101A}\mathrm{PersonA}_i + \pi_{102A}\mathrm{PersonB}_i + u_{10Ai}$ (4.1), $\gamma_{11Ai} = \pi_{110A}$ (4.2), $\gamma_{12Ai} = \pi_{120A}$ (4.3), $\gamma_{20Ai} = \pi_{200A} + \pi_{201A}\mathrm{PersonA}_i + \pi_{202A}\mathrm{PersonB}_i + u_{20Ai}$ (4.4), $\gamma_{21Ai} = \pi_{210A}$ (4.5), $\gamma_{22Ai} = \pi_{220A}$ (4.6), $\gamma_{30Ai} = \pi_{300A} + \pi_{301A}\mathrm{PerssonA}_i + \pi_{302A}\mathrm{PersonB}_i$ (4.7), $\gamma_{31Ai} = \pi_{310A}$ (4.8), $\gamma_{32Ai} = \pi_{320A}$ (4.9), $\gamma_{40Ai} = \pi_{400A}$ (4.10), $\gamma_{50Ai} = \pi_{500A}$ (4.11), $\gamma_{10Bi} = \pi_{100B} + \pi_{101B}\mathrm{PersonA}_i + \pi_{102B}\mathrm{PersonB}_i + u_{10Bi}$ (4.12), $\gamma_{11Bi} = \pi_{110B}$ (4.13), $\gamma_{12Bi} = \pi_{120B}$ (4.14), $\gamma_{20Bi} = \pi_{200B} + \pi_{201B}\mathrm{PersonA}_i + \pi_{202B}\mathrm{PersonB}_i + u_{20Bi}$(4.15), $\gamma_{21Bi} = \pi_{210B}$(4.16), $\gamma_{22Bi} = \pi_{220B}$ (4.17), $\gamma_{30Bi} = \pi_{300B} + \pi_{301B}\mathrm{PersonA}_i + \pi_{302B}\mathrm{PersonB}_i$ (4.18), $\gamma_{31Bi} = \pi_{310B}$ (4.19), $\gamma_{32Bi} = \pi_{320B}$ (4.20), $\gamma_{40Bi} = \pi_{400B}$ (4.21), $\gamma_{50Bi} = \pi_{500B}$ (4.22), and finally (4.23),

$$\begin{pmatrix} u_{10Ai} \\ u_{10Bi} \\ u_{20Ai} \\ u_{20Bi} \end{pmatrix} \sim MVN\left(\mathbf{0}, \begin{pmatrix} \sigma^2_{1A} & & & \\ \sigma_{1A1B} & \sigma^2_{1B} & & \\ \sigma_{1A2A} & \sigma_{1B2A} & \sigma^2_{2A} & \\ \sigma_{1A2B} & \sigma_{1B2B} & \sigma_{2A2B} & \sigma^2_{2B} \end{pmatrix}\right)$$

where, in Eq. 4.1, π_{100A} is the prototypical value of inertia effect for Task A. Positive π_{101A} indicates that person-specific inertia effects γ_{10Ai} increase with larger positive deviations from the sample-level mean. Person-level moderations were included for both Task A (see Eqs. 4.1, 4.4, 4.7) and Task B (see Eqs. 4.12, 4.15, 4.18).

For attentional inertia (see Eqs. 4.1 and 4.15) and attentional residue (see Eqs. 4.4 and 4.12) effects, random effects were included to allow for individual differences. The four random effects (u_{10Ai}, u_{20Ai}, u_{10Bi}, u_{20Bi}) are assumed to follow a multivariate normal distribution with an unstructured covariance structure (see Eq. 4.23). Of particular interest is the value of the σ_{1A1B} and σ_{2A2B} parameters, which indicate the correlation between attentional inertia of Task A and attentional residue from Task A to Task B and the correlation between attentional inertia of Task B and attentional residue from Task B to Task A. These parameters indicate the relations between carrying over and reconfiguring mental resources for an initial task and hypothesized to be positive by the bottleneck theory.

In practice, Equations 2.1 to 4.23 were combined and estimated simultaneously in a single multilevel model using dummy variables that indicate whether the observation was A or B (Bolger & Laurenceau, 2013). All models were estimated using the "nlme" library in R (Pinheiro & Bates, 2000). Further details are available from https://bit.ly/u4pce.

Results

Quantifying Trial-Level Variability

From the hierarchical variance decomposition, we found that variance in the dual-task RT performance was mostly attributed to trial-to-trial fluctuations and person-level differences. For Task A, trial-level variance accounted for 44% of the total variance in RT, person-level variance accounted for 46%, and session-level variance accounted for 10%. For Task B, trial-, person- and session-level variance accounted for 57%, 30%, and 12% of the total variance.

Attentional Inertia and Residue Effects

We fit and compared the fit of three nested multilevel VARs structured to examine if and how moderations at the trial, session, and person level might help explain the within- and between-task variability of RT. We focus our interpretation on the full model which provided the best fit ($\chi^2(12)$ = 3985.855, $p < .001$) and included all three-level moderations.

Our results suggest that both positive attentional inertia and positive attentional residue manifest in dual-tasking performance blocks. Positive inertia effects for both Task A (π_{100A} = 0.089, $p < .001$) and Task B (π_{200B} = 0.086, $p <$ .001) indicate that when an average person performing a prototypical session (i.e., both person- and session-level moderations are zero) is slower than expected on a given trial, they also tend to be slower on the next trial of the same task. Similarly, positive residue effects in both directions, from Task A to B (π_{100B} = 0.038, $p < .001$) and from Task B to A (π_{200A} = 0.064, $p < .001$), indicate that when a person's performance for one task on the given trial is slower than expected (i.e., RT is longer than the person's session average), they also tend to be slower on the next trial of the other task. In sum, these four positive coefficients suggest and support that attentional settings from an initial task persist, both within and between tasks.

Our model facilitates examination of how this dual-task interference is moderated by session- and person-level differences in performance. Specifically, in sessions when Task A performance was slower than usual, both inertia for Task A and residue from Task A to B increased (π_{110A} = 0.243, $p < .001$; π_{110B} = 0.039, $p < .001$); in complement, inertia for Task B and residue from Task B to A decreased (π_{210A} = -0.174, $p < .001$; π_{210B} = -0.062, $p < .001$). We found mixed findings for session-level performance for Task B (SessionB), but all coefficients were closer to zero than those related to session-level performance for Task A (SessionA). However, interestingly, there was no evidence that attentional inertia or residue were moderated by person-level differences in performance speed (p's > .05).

Our model also shows that SOA moderates dual-tasking performance in different ways. For example, Task B performance was faster (π_{300B} = -0.343, $p < .001$) and Task A performance was slightly slower (π_{300A} = 0.028, $p < .001$) on trials where Task A was presented first and Task B appeared only after an SOA. Specifically, attentional inertia effects increased for Task A (π_{400A} = 0.056, $p < .001$), indicating that attentional control settings were more persistent when the stimulus onset of Task B was delayed. In contrast, these inertia effects decreased for Task B (π_{500B} = -0.118, $p < .001$). Residue effects from Task A increased with SOA (π_{400B} = 0.035, $p < .001$) but those from Task B decreased with SOA (π_{400A} = -0.053, $p < .001$).

Correlation of Inertial and Residue Effects

Overall positive random effects suggest that there is a high overlap between inertia and residue effects at the person level. While attentional inertia and residue effects from the same task (e.g., inertia A → A and residue A → B) showed positive correlations (σ_{1A1B} = 0.347 from Task A; σ_{2A2B} = 0.247 from Task B), those effects from different tasks (e.g., inertia A → A and residue B → B) were negatively correlated (σ_{1A2A} = -0.311; σ_{1B2B} = -0.421).

Discussion

We employed two modeling approaches to examine how attentional inertia and residue effects manifest at the person level. In the first approach, we fitted hierarchical variance decomposition models to partition variance into three levels, examining how much trial-level variability accounts for the total variance. In the second approach, we fitted mlVARs wherein inertia and residue effects are represented as the lagged and cross-lagged relations of RT. By employing multilevel VARs, we assessed how these person-specific parameters are correlated in testing bottleneck theory. Overall, our results confirm existing findings and expand the literature into multilevel and dyadic analysis. We now discuss how our analysis addresses the three specific aims.

First, our hierarchical variance decomposition analysis demonstrates that trial-level variance accounts for a significant portion of the total variance and thus should be considered in the analysis. Of the total variance in RT, trial-level variance accounted for 44% (Task A) and 57% (Task B), while person-level variance accounted for 46% (Task A) and 30% (Task B). This suggests that traditional modeling approaches – where the RT data are averaged at the session or person level prior to analysis to remove trial-level "noise" – might fail to capture systematic patterns in the within-task, trial-to-trial variability. Furthermore, session-level variance accounted for the smallest portion of all three levels (10% for Task A; 12% for Task B); this also suggests that averaging at the session level (e.g., Brose et al., 2012; Naefgen et al., 2023) might not be sufficient for within-person level analysis. Taken together, our variance decomposition analysis provides a rationale of why we fitted multilevel VARs at the trial level to examine how attentional inertia and residue manifest in in dual-tasking performance.

Second, mlVAR results indicated that all four attentional inertia and residue effects are positive. These results align with previous findings that attentional control settings are persistent both within and between tasks. Our analysis of session- and person-level moderations also explains how this type of interference might change with session-to-session fluctuations and person-to-person differences. Notably, attentional inertia and residue effects increase when session-level performance is slower than expected, particularly for the initial task (Task A). This finding is also consistent with the existing literature that attentional control settings become more persistent when a participant invests more time or cognitive effort into an initial task. In contrast, we found that this persistence might be weaker for the secondary task (Task B). Finally, the null coefficients of moderations at the person level suggest that extent of attentional inertia and residue – that manifest at the trial level – does not differ systematically across generally high- and low-performing individuals.

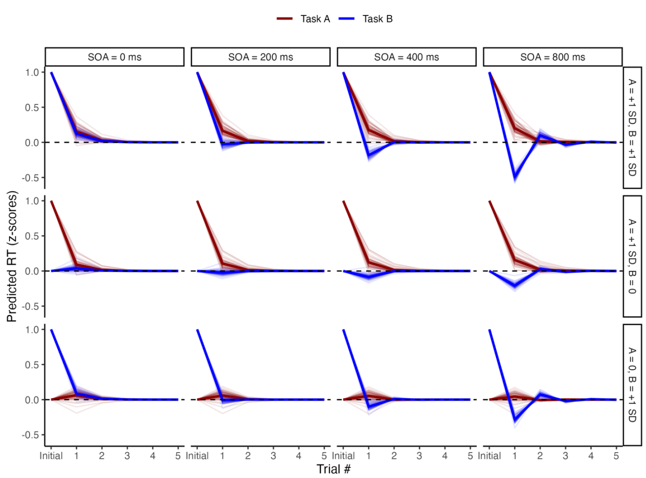

Figure 3: mlVAR predictions at the person level (shown as thin lines) and at the sample level (shown as thick lines).

Aligning with the PRP effect, our results indicated that longer SOAs are generally associated with faster Task B performance but slightly slower Task A performance. Additionally, Figure 3 illustrates how increasing SOA (from left to right) moderates attentional inertia and residue effects for a prototypical session and an average person. Overall, the decreasing trends across trials suggest that a slower performance on an initial trial gradually returns to the baseline. SOA facilitates this recovery, particularly for the secondary Task B. The blue line graphs for Task B in the first and third rows are steeper than the red line graphs for Task A in the first and second rows, and this pattern is consistent with our finding that inertia effects for Task B decreased whereas those for Task A increased, with longer SOAs. By contrast, the red line graph for Task A in the third row is flat even as the RT for Task B decreases more sharply at longer SOAs. This observation is consistent with the finding that residue effects from Task B decreased with SOA whereas those from Task A increased with SOA.

Third, these attentional inertia and residue effects are positively correlated, especially for those originating from the same initial task. This supports the bottleneck theory, suggesting that both effects are manifestations of the same structural reconfiguration speed and that a single channel governs the two possible directional influences of the initial task. However, the negative correlations between two direction influences flowing into the same second task suggest a within-task competition from attentional control settings, aligning with the shared capacity theory. Taken together, our findings are largely consistent with the bottleneck theory, but they also highlight the complex dynamics of these bidirectional influences.

Limitations and Future Outlook

Our mlVAR approach demonstrates the viability of simultaneously examining attentional inertia and residue effects. We discuss three limitations and future directions that can be useful to further elaborate on how these types of interference manifest. First, because our model is based on the stationarity and normality assumptions after removing outliers, future research should employ more flexible modeling that is robust to these assumptions and outliers (Craigmile et al., 2010; Ratcliff, 1972). Second, while our results showed positive inertia and residue parameters, we did not formally test whether these parameters differ (Gade et al., 2021). For example, are attentional inertia effects greater than attentional residue effects? Are attentional control settings during dual-task blocks more persistent than those during single-task blocks? How does task difficulty asymmetry between Task A and Task B manifest? Future studies may employ a Bayesian modeling framework to address these questions (Wagenmakers et al., 2018). Third, we lack a mechanistic explanation of why attentional inertia or residue manifests (e.g., latent variable modeling, dynamical systems approach, Ernst & Haslbeck, 2025; Gates & Liu, 2016).

Conclusion

While research shows that attentional control settings may carryover or spillover over time, many findings often rely on cross-sectional data and analysis of group-level mean differences. Using hierarchical decomposition and mlVAR modeling approaches, we introduced a framework that can capture bidirectional influences across two tasks while also accommodating the nested structure of multi-trial, multi-session data. Our results suggest that these settings are indeed persistent both within (positive inertia) and between (positive residue) tasks. Overall positive correlations among these parameters, particularly those correlations originating from the same initial task, support bottleneck theory.

References

Allport, A., Styles, E. A., & Hsieh, S. (1994). Shifting intentional set: Exploring the dynamic control of tasks. In C. Umiltà & M. Moscovitch (Eds.), *Attention and performance XV: Conscious and nonconscious information processing* (pp. 421–452). MIT Press.

Bolger, N., & Laurenceau, J.-P. (2013). *Intensive longitudinal methods: An introduction to diary and experience sampling research*. The Guilford Press.

Bringmann, L. F., Vissers, N., Wichers, M., Geschwind, N., Kuppens, P., Peeters, F., Borsboom, D., & Tuerlinckx, F. (2013). A network approach to psychopathology: New insights into clinical longitudinal data. *PloS ONE, 8*(4), e60188. https://doi.org/10.1371/journal.pone.0060188

Brose, A., Schmiedek, F., Lövdén, M., & Lindenberger, U. (2012). Daily variability in working memory is coupled with negative affect: The role of attention and motivation. *Emotion, 12*(3), 605–617. https://doi.org/10.1037/a0024436

Chow, C. M., Claxton, S. E., & van Dulmen, M. H. M. (2015). Testing dyadic mechanisms the right way: A primer into moderated actor–partner interdependence model with latent variable interactions. *Emerging Adulthood, 3*(6), 421–433. https://doi.org/10.1177/2167696815605728

Craigmile, P. F., Peruggia, M., & Zandt, T. V. (2010). Detrending response time series. In S.-M. Chow, E. Ferrer, & F. Hsieh (Eds.), *Statistical methods for modeling human dynamics: An interdisciplinary dialogue* (pp. 213–240). Routledge/Taylor & Francis Group.

Ernst, A. F., & Haslbeck, J. M. B. (2025). Modeling qualitative between-person heterogeneity in time series using latent class vector autoregressive models. *Behavior Research Methods, 58*(1), 28. https://doi.org/10.3758/s13428-025-02909-7

Folk, C. L., Remington, R. W., & Johnston, J. C. (1992). Involuntary covert orienting is contingent on attentional control settings. *Journal of Experimental Psychology. Human Perception and Performance, 18*(4), 1030–1044. https://doi.org/10.1037/0096-1523.18.4.1030

Gade, M., Declerck, M., Philipp, A. M., Rey-Mermet, A., & Koch, I. (2021). Assessing the evidence for asymmetrical switch costs and reversed language dominance effects – a meta-analysis. *Journal of Cognition, 4*(1), 55. https://doi.org/10.5334/joc.186

Gates, K. M., & Liu, S. (2016). Methods for quantifying patterns of dynamic interactions in dyads. *Assessment, 23*(4), 459–471. https://doi.org/10.1177/1073191116641508

Gatzke-Kopp, L., & Ram, N. (2018). Developmental dynamics of autonomic function in childhood. *Psychophysiology, 55*(11), e13218. https://doi.org/10.1111/psyp.13218

Hamaker, E. L. (2012). Why researchers should think "within-person": A paradigmatic rationale. In M. R. Mehl & T. S. Conner (Eds.), *Handbook of research methods for studying daily life* (pp. 43–61). The Guilford Press.

Hamaker, E. L., Asparouhov, T., Brose, A., Schmiedek, F., & Muthén, B. (2018). At the frontiers of modeling intensive longitudinal data: Dynamic structural equation models for the affective measurements from the COGITO study. *Multivariate Behavioral Research, 53*(6), 820-841. https://doi.org/10.1080/00273171.2018.1446819

Kaptein, N. A., Theeuwes, J., & Van der Heijden, A. H. C. (1995). Search for a conjunctively defined target can be selectively limited to a color-defined subset of elements. *Journal of Experimental Psychology: Human Perception and Performance, 21*(5), 1053. https://doi.org/10.1037/0096-1523.21.5.1053

Kenny, D. A., & Ledermann, T. (2010). Detecting, measuring, and testing dyadic patterns in the actor–partner interdependence model. *Journal of Family Psychology, 24*(3), 359–366. https://doi.org/10.1037/a0019651

Klapp, S. T., Maslovat, D., & Jagacinski, R. J. (2019). The bottleneck of the psychological refractory period effect involves timing of response initiation rather than response selection. *Psychonomic Bulletin & Review, 26*(1), 29–47. https://doi.org/10.3758/s13423-018-1498-6

Koch, I., Poljac, E., Müller, H., & Kiesel, A. (2018). Cognitive structure, flexibility, and plasticity in human multitasking—An integrative review of dual-task and task-switching research. *Psychological Bulletin, 144*(6), 557–583. https://doi.org/10.1037/bul0000144

Koval, P., Kuppens, P., Allen, N. B., & Sheeber, L. (2012). Getting stuck in depression: The roles of rumination and emotional inertia. *Cognition & Emotion, 26*(8), 1412–1427. https://doi.org/10.1080/02699931.2012.667392

Kuppens, P., & Verduyn, P. (2017). Emotion dynamics. *Current Opinion in Psychology, 17*, 22–26. https://doi.org/10.1016/j.copsyc.2017.06.004

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. *Journal of Econometrics*, *54*(1-3), 159-178. https://doi.org/10.1016/0304-4076(92)90104-Y

Leber, A. B., & Egeth, H. E. (2006). It's under control: Top-down search strategies can override attentional capture. *Psychonomic Bulletin & Review, 13*(1), 132–138. https://doi.org/10.3758/BF03193824

Leroy, S. (2009). Why is it so hard to do my work? The challenge of attention residue when switching between work tasks. *Organizational Behavior and Human Decision Processes*, 109(2), 168–181. https://doi.org/10.1016/j.obhdp.2009.04.002

Lien, M.-C., McCann, R. S., Ruthruff, E., & Proctor, R. W. (2005). Dual-task performance with ideomotor-compatible tasks: Is the central processing bottleneck intact, bypassed, or shifted in locus? *Journal of Experimental Psychology: Human Perception and Performance, 31*(1), 122–144. https://doi.org/10.1037/0096-1523.31.1.122

LoBraico, E. J., Brinberg, M., Ram, N., & Fosco, G. M. (2020). Exploring processes in day-to-day parent–adolescent conflict and angry mood: Evidence for circular

causality. *Family Process, 59*(4), 1706–1721. https://doi.org/10.1111/famp.12506
Longman, C. S., Lavric, A., Munteanu, C., & Monsell, S. (2014). Attentional inertia and delayed orienting of spatial attention in task-switching. *Journal of Experimental Psychology: Human Perception and Performance, 40*(4), 1580–1602. https://doi.org/10.1037/a0036552
Masten, A. S., & Cicchetti, D. (2010). Developmental cascades [Editorial]. *Development and Psychopathology, 22*(3), 491–495. https://doi.org/10.1017/S0954579410000222
McCann, R. S., & Johnston, J. C. (1992). Locus of the single-channel bottleneck in dual-task interference. *Journal of Experimental Psychology: Human Perception and Performance, 18*(2), 471–484. https://doi.org/10.1037/0096-1523.18.2.471
Molenaar, P. C. M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement: Interdisciplinary Research and Perspectives, 2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1
Monsell, S. (2003). Task switching. *Trends in Cognitive Sciences, 7*(3), 134–140. https://doi.org/10.1016/s1364-6613(03)00028-7
Naefgen, C., Blech, C., Kriechbaumer, M., Haider, H., Ram, N., & Gaschler, R. (2023). Between-and within-subject covariance perspectives matter for investigations into the relationship between single-and dual-tasking performance. *Methods in Psychology, 8*, 100110. https://doi.org/10.1016/j.metip.2023.100110
Navon, D., & Gopher, D. (1979). On the economy of the human-processing system. *Psychological Review, 86*(3), 214–255. https://doi.org/10.1037/0033-295X.86.3.214
Pashler, H. (1984). Processing stages in overlapping tasks: Evidence for a central bottleneck. *Journal of Experimental Psychology: Human Perception and Performance, 10*(3), 358–377. https://doi.org/10.1037/0096-1523.10.3.358
Pashler, H. (1994). Dual-task interference in simple tasks: Data and theory. *Psychological Bulletin, 116*(2), 220–244. https://doi.org/10.1037/0033-2909.116.2.220
Pinheiro, J. C. & Bates, D. M. (2000). *Mixed-effects models in S and S-PLUS*. Springer.
Ratcliff, R. (1993). Methods for dealing with reaction time outliers. *Psychological Bulletin, 114*(3), 510–532. https://doi.org/10.1037/0033-2909.114.3.510
Richards, J. E., & Anderson, D. R. (2004). Attentional inertia in children's extended looking at television. In R. V. Kail (Ed.), *Advances in child development and behavior* (Vol. 32, pp. 163–212). Elsevier Academic Press. https://doi.org/10.1016/S0065-2407(04)80007-7
Rogers, R. D., & Monsell, S. (1995). Costs of a predictable switch between simple cognitive tasks. *Journal of Experimental Psychology: General, 124*(2), 207–231. https://doi.org/10.1037/0096-3445.124.2.207
Rossi, A. F., & Paradiso, M. A. (1995). Feature-specific effects of selective visual attention. *Vision Research, 35*(5), 621–634. https://doi.org/10.1016/0042-6989(94)00156-G
Strobach, T. (2020). The dual-task practice advantage: Empirical evidence and cognitive mechanisms. *Psychonomic Bulletin & Review, 27*(1), 3–14. https://doi.org/10.3758/s13423-019-01619-4
Telford, C. W. (1931). The refractory phase of voluntary and associative responses. *Journal of Experimental Psychology, 14*(1), 1–36. https://doi.org/10.1037/h0073262
Thompson, C., Howting, L., & Hills, P. (2015). The transference of visual search between two unrelated tasks: Measuring the temporal characteristics of carry-over. *Quarterly Journal of Experimental Psychology, 68*(11), 2255-2273. https://doi.org/10.1080/17470218.2015.1013042
Tombu, M., & Jolicoeur, P. (2003). A central capacity sharing model of dual-task performance. *Journal of Experimental Psychology: Human Perception and Performance, 29*(1), 3–18. https://doi.org/10.1037//0096-1523.29.1.3
Tombu, M., & Jolicoeur, P. (2005). Testing the predictions of the central capacity sharing model. *Journal of Experimental Psychology: Human Perception and Performance, 31*(4), 790–802. https://doi.org/10.1037/0096-1523.31.4.790
Wagenmakers, E. J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R., Gronau, Q. F., Šmíra, M., Epskamp, S., Matzke, D., Rouder, J. N., & Morey, R. D. (2018). Bayesian inference for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic Bulletin & Review, 25*(1), 35–57. https://doi.org/10.3758/s13423-017-1343-3
Welford, A. T. (1952). The 'psychological refractory period' and the timing of high-speed performance—a review and a theory. *British Journal of Psychology, 43*, 2–19. https://doi.org/10.1111/j.2044-8295.1952.tb00322.x
Welford, A. T. (1959). Psychomotor performance. In J. E. Birren (Ed.), *Handbook of aging and the individual* (pp. 562–613). University of Chicago Press.
Wendt, D., Hietkamp, R. K., & Lunner, T. (2017). Impact of noise and noise reduction on processing effort: a pupillometry study. *Ear and Hearing, 38*(6), 690–700. https://doi.org/10.1097/AUD.0000000000000454