Variance (un)explained: Experimental conditions and temporal dependencies explain similarly small proportions of reaction time variability in perceptual and cognitive tasks

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Abstract

Any series of sensorimotor actions shows fluctuations in speed and accuracy from repetition to repetition, even when the sensory input and the motor output requirements remain identical over time. Such fluctuations are particularly prominent in reaction time (RT) series from laboratory neurocognitive tasks. Despite their omnipresent nature, trial-to-trial fluctuations remain poorly understood. Here, we systematically analysed RT series from various neurocognitive tasks, quantifying how much of the total trial-to-trial RT variance can be explained by three sources of variability that are frequently investigated in behavioural and neuroscientific research: 1) the experimental conditions, which are commonly employed to induce systematic patterns in variability, 2) short-term temporal dependencies such as the autocorrelation between subsequent trials, and 3) long-term temporal trends over entire experimental blocks and sessions. Furthermore, we examined to what extent the explained variances by these sources are shared or unique. In total, we analysed 1913 unique RT series from 30 different cognitive control and perception-based tasks. On average, the three sources together explained only about 8-17% of the total variance. The experimental conditions explained on average about 2.5-3.5%, but did not share explained variance with temporal dependencies. Thus, the largest part of the trial-to-trial fluctuations in RT remained unexplained by the three variability sources that are typically analysed here. These may be attributable to observable endogenous factors, such as ongoing fluctuations in brain activity and bodily states, though some extent of randomness may be a feature of behaviour rather than just nuisance.

Key words: intra-individual variability; spontaneous fluctuations; endogenous and exogenous factors; measurement error;

Introduction

Any sensorimotor action we repeatedly execute, such as chopping vegetables, moving to a beat, or performing a defined move in sports, is characterised by variability in speed and accuracy from repetition to repetition. Such ***trial-to-trial variability*** is evident in typical laboratory tasks in which such sensorimotor actions are precisely recorded: although these tasks strictly control the environmental context with a limited set of sensory inputs and motor outputs, participants' responses still fluctuate considerably from trial to trial (Figure 1B). These fluctuations remain poorly understood: most of the time, we cannot explain why a participant responds fast or slow in a particular trial, and why they commit an error in one but not another. In other words, the predictability of individual actions over time appears highly limited. However, this predictability is important for empirical sciences in general (Yarkoni & Westfall, 2017), and also for daily life – for example, being able to predict why people sometimes respond fast (or slow) in critical tasks such as operating air control or driving a car (e.g., Baldwin et al., 2017). Here, we systematically examine trial-to-trial variability across a range of tasks that are commonly used in cognitive neuroscience. We focus on two well-documented constructs that both contribute to trial-to-trial variability, but which are typically studied separately: experimental conditions, which researchers may use to cause specific patterns in behavioural data, and task-unrelated fluctuations of behaviour over time, which may occur between subsequent trials and across blocks of trials.

By implementing experimental conditions, researchers aim to induce systematic differences in behaviour to gain an understanding of specific neurocognitive mechanisms. However, systematic differences between conditions are often difficult to identify in individual data series. This is illustrated in Figure 1 for the Flanker task, a well-known paradigm for conflict processing. Fluctuations beyond those induced by the experimental conditions are usually considered 'noise' and are removed during data analysis by computing condition means or other forms of summary statistics. The experimental questions are then answered at the level of these means (e.g., "are participants *overall* slower on incongruent than on congruent trials?"). Visualising the distribution of reaction times (RT) for a single participant reveals high variance within conditions (Figure 1C), which is often much larger than

variance between conditions. Indeed, systematic group-level analyses of cognitive conflict tasks show that the between-subject variance of the difference in mean RT between congruent and incongruent conditions is on average about seven times smaller than the within-subject RT variance (Rouder et al., 2019). While a large fraction of the within-subject variability in typical neurocognitive tasks is thus independent of the experimental conditions, most studies do not quantify or report what proportion of the total variance is explained by the experimental effects. To address this question, the current study offers a systematic examination of the trial-to-trial variability that is explained by the experimental condition across a range of tasks.

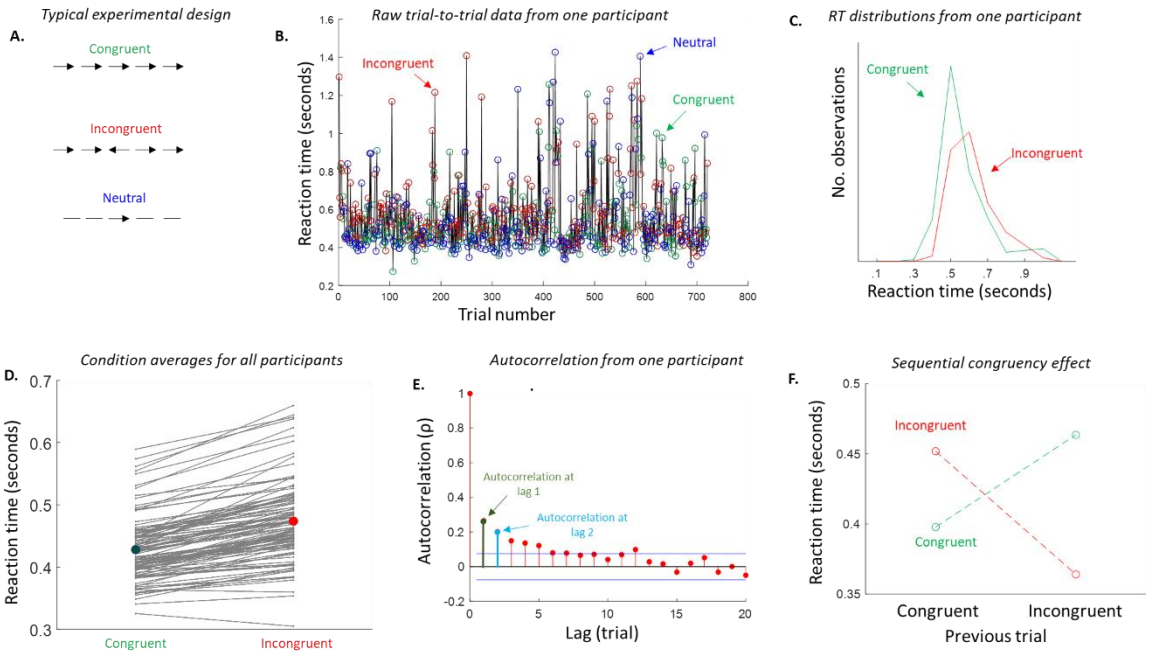

Figure 1. Example of a typical experimental study using the Flanker task as example. ***A.*** *Participants discriminate the direction of the middle arrow while the flankers can be identical (congruent), contradictory (incongruent), or neutral. A researcher is examining whether participants are faster in the congruent and slower in the incongruent condition.* ***B.*** *Reaction time (RT) data from one participant on the Flanker task across all trials, based on data from Hedge et al. (2017). This reveals large fluctuations over trials across all experimental conditions (green, red, blue).* ***C.*** *RT distributions for the congruent and incongruent condition for one participant. The participant is faster in the congruent compared to the incongruent condition, but*

variability within each experimental condition is much larger than the average difference between experimental conditions. ***D.*** *Means on the group level for congruent and incongruent conditions, with each line representing the RT of one participant. Nearly all participants are on average faster in the congruent than in the incongruent condition, in confirmation of the initial research question.* ***E.*** *Autocorrelation in RT series from one participant. Lag refers to the distance between trial numbers – e.g., lag one represents the autocorrelation between trial n and trial n-1.* ***F.*** *The effect of experimental conditions on RT in each trial is modulated by the experimental condition on the previous trial – a phenomenon known as the sequential congruency effect.*

Another line of research emphasises that the trial-by-trial variability of behaviour is not random, but exhibits structured dependencies over time (e.g., Gilden, 2001; Van Orden et al., 2003; Perquin et al., 2023; Torre et al., 2019; Torre & Wagenmakers, 2009; Wagenmakers et al., 2004; Welford, 1968). For example, most RT series show positive autocorrelations (Figure 1E), indicating that fast RTs are more likely followed by fast than slow RTs, and vice versa. Certain forms of temporal dependencies can be caused by the order of experimental conditions and are hence induced exogenously (Duthoo et al., 2014; Egner, 2017; Fritsche et al., 2017; Gratton et al., 1992; Kayser & Kayser, 2018; Kiyonaga et al., 2017). An example is the 'sequential congruency' (alternatively, 'Gratton') effect, which denotes the phenomenon that participants respond faster if the previous trial was of the same condition as the current one (e.g., both congruent in the Flanker task; Figure 1F). However, temporal dependencies are also present in tasks in which the same sensorimotor action is performed repeatedly and without any changes in experimental condition, such as tapping to a fixed interval (e.g., Chen et al., 2002; Lemoine et al., 2006; Madison, 2001; Perquin et al., 2023). Because the external environment remains the same, such dependencies must be driven endogenously – i.e., arising from fluctuations in the internal system. Such endogenous dependencies can emerge across multiple time scales, and are important for the predictability of trial-to-trial fluctuations, as high dependency implies high predictability. Their interpretation is very different from the exogenously-driven temporal effects: the latter reflects after-effects of external stimuli, while the former may reflect temporal

dynamics in spontaneous neural fluctuations (e.g., Palva et al., 2013; Smit et al, 2013). In the current study, we therefore quantified exogenous temporal effects in the form of experimental conditions separately from endogenous temporal dependencies, allowing for a direct comparison of these sources of variability.

Here, we systematically examined the variance in the trial-to-trial variability of RTs explained by the experimental conditions and endogenous temporal trends across a sample of 1913 unique manual button press RT series. We focused on RT because it provides a continuous and rich measure of behavioural variability. The data were taken from publicly available resources and our own previous work and comprised tasks commonly used in the field of cognitive control (e.g., Flanker and Stroop tasks; termed ‘congruency-based’ in the following) and perception (e.g., detection of stimuli in noisy contexts and orientation discrimination; termed ‘perception-based’). We quantified how much of the total RT variability is explained by: 1) the experimental conditions, 2) short-range temporal dependencies between triplets of subsequent trials, and 3) long-range temporal dependencies across entire experimental blocks.

Changes in behaviour over the course of an experiment may or may not be related to changes in response to different conditions. For example, if a participant becomes slower over time due to increased drowsiness, it is possible that this affects difficult conditions (e.g., incongruent) more than easier ones (e.g., congruent), which would be reflected in an increase in the RT difference between conditions over time. Likewise, if a participant becomes better at responding to difficult but not to easier conditions with more practice, the difference between conditions decreases during the experiment. Both cases would be reflected in overlapping explained variance between experimental conditions and temporal dependencies. Indeed, in vigilance studies, responses to rare but not to frequent targets get slower and less accurate over the course of an experiment (Karimi-Rouzbahani et al., 2021; Temple et al., 2000), but it remains unclear whether such trends also exist in tasks in which the conditions are balanced and (pseudo-)randomly presented. Aside from experimental conditions, one might also expect common explained variance between short- and long-range temporal dependencies: for example both dependencies could be characterisations of the same phenomenon, such as short-term autocorrelations producing longer trends. To address these questions of overlapping variance, we

therefore systematically examine to what extent the explained variance of the three sources are shared or unique using variance partitioning.

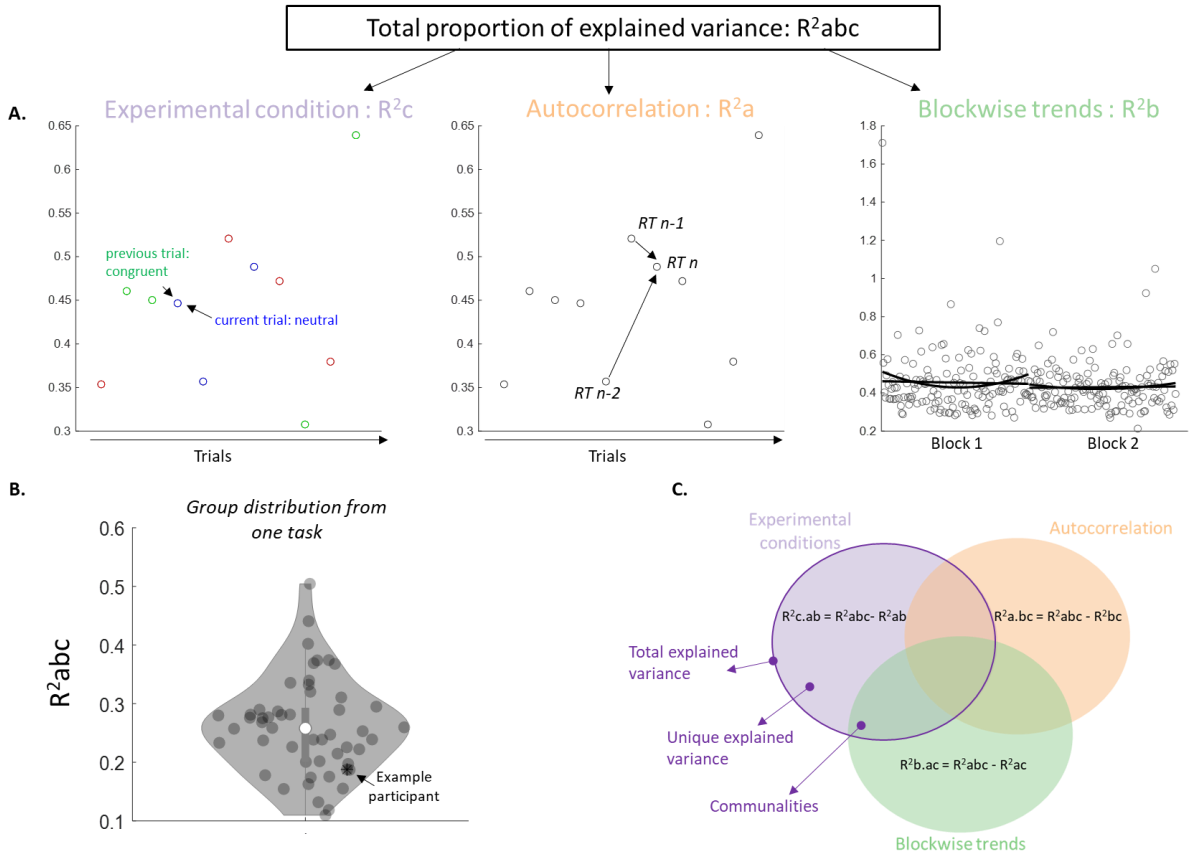

Figure 2. Outline of the data analysis. ***A.*** *For each participant, GLMs were fit on RT for each of the three sources of interest: 1) experimental conditions (including the current and previous trial as predictors; left), 2) autocorrelation (including the previous and second-to-last trial; middle), and 3) linear and quadratic blockwise trends (including blockwise trial numbers as predictors; right) to extract the explained variance (R^2) for each source. Furthermore, we fit a GLM that combined these individual predictors ("full model") to extract the variance explained by all three sources together (R^2_{abc}).* ***B.*** *The total proportion of explained variance was extracted for each participant for each of the sources separately (R^2_a, R^2_b, R^2_c) as well as for all three sources combined (R^2_{abc}). Distributions of explained variance are examined on the group level, showing R^2_{abc} as an example for one task.* ***C.*** *The unique explained variance for each source of interest is calculated by subtracting the explained variance of the other two components from the overall explained variance. The*

communalities in turn refers to the explained variance that is shared by each combination of sources.

Results

We analysed RT time series from a total of 30 datasets. Sixteen of them were from congruency-based tasks (1563 unique RT series in total, N = 1445 after exclusion; Table 2) and 14 were from perception-based tasks (350 RT series, N = 318 after exclusion; Table 3). Our analysis centred around three sources of trial-to-trial variability, with each source consisting of multiple predictors (Figure 2A). The first source is the 'experimental conditions', operationalised as the condition of the current and previous trial to capture the immediate experimental effects and the sequential condition effects. The second source is the 'autocorrelation', operationalised as the autocorrelation at lag 1 (= previous trial) and lag 2 (= two trials back) to capture short-range dependencies (middle). The third source is the 'blockwise trends', operationalised as trial-wise linear and quadratic trends across the experimental blocks to capture long-range dependency (right).

Explained within-subject variance is low

To calculate the proportion of explained variance (Figure 2B), Generalised Linear Models were fit separately for each participant, regressing RT as dependent variable. The total, unique and common proportions of explained variance were extracted for each source of variance (Figure 2C). We corrected variance estimates by subtracting explained variance obtained from randomly shuffled data (see Methods). To examine consistency across tasks, we calculated the group median for each dataset.

Figure 3 shows the explained variance for all sources combined, and each source considered individually, separately for congruency- (top rows) and perception-based (bottom) tasks. The respective median values are provided in Table 1. On the task-level, the three sources collectively explained on average 1/7 to 1/10 of the total trial-to-trial variance. Thus, the largest part of the variance remained unexplained.

Numerically, median explained variance was higher for the perception- compared to the congruency-based tasks, but this difference was not as pronounced on the task-level.

The total proportion of variance (left panels) explained by the experimental conditions was less than a third of the total explained variance; in other words, temporal dependencies explained more variance than experimental conditions. Moreover, the total contribution of experimental conditions was <10% for 1308 out of all 1445 analysed RT series (91%) in the congruency-based tasks, and for 253 out of 318 RT series (80%) in the perception-based tasks. Numerically, blockwise trends explained the highest proportion of variance.

The unique variance (right panels) explained by autocorrelation and blockwise trends were numerically substantially lower compared to their total explained variances (see Table 1). This reduction was only minimal for the experimental conditions.

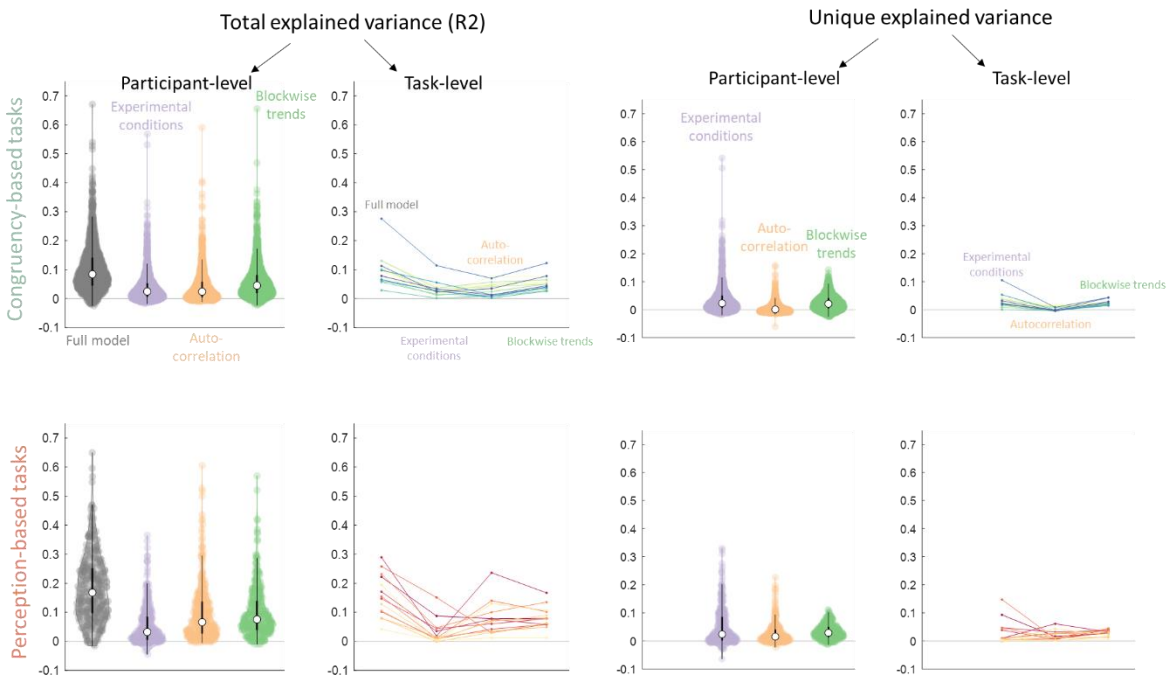

Figure 3. Total explained variance (left panels) and unique explained variance (right panels) in congruency-based tasks (top rows) and perception-based tasks (bottom rows). On the participant-level, each dot represents one RT series, the white circle represents the median of the distribution, and the width of the dot cloud indicates

distribution density – by the three sources combined (full model or R^2_{abc}; grey) as well as separately (purple, orange, and green for experimental condition R^2_c, autocorrelational R^2_a, and blockwise trends R^2_b sources respectively) as estimated by the participant-wise GLMs. On the task-level, each line represents the median across participants for each task separately across the three sources. Negative values indicate instances in which the predictors explained less variance than random noise.

Table 1. Median total and unique explained variance (plus standard deviation) on the participant-level (corresponding to the white dots in the violin plots on Figure 3). Highest values of explained variance across the three sources are displayed in bold.

	Total explained variance	**Unique explained variance**
Congruency-based		
All sources	8.42 (9.5)	
Experimental condition	2.44 (4.6)	**2.27** (4.38)
Autocorrelation	2.38 (5.2)	0.001 (1.93)
Blockwise trends	**4.50** (6.1)	2.09 (3.5)
Perception-based		
All sources	16.79 (15.3)	
Experimental condition	3.25 (7.9)	2.37 (8.2)
Autocorrelation	6.63 (10.8)	1.52 (3.6)
Blockwise trends	**7.56** (9.9)	**2.86** (3.6)

Short- and long-term dependency, but not condition, share explained variance

We also extracted the amount of explained variance that was shared between sources (i.e., communality; overlapping parts of the circles in Figure 2C). There was virtually no overlap between the variance explained by the experimental conditions and the temporal dependencies. For example, the variance commonly explained by experimental conditions and autocorrelation (blue) was on average .0001, hence

amounting to less than .01% of the total within-subject variance. The other communalities involving experimental condition (grey and pink) were also negligible, both in the congruency- and perception-based tasks. The median communality value between autocorrelation and blockwise trends was 4.2% and 2.0% for congruency- and perception-based tasks, respectively. This indicates that shared explained variance between short- and long-term dependencies amounts to about 2-4%in the total trial-to-trial variance. Overall, explained variance originating from experimental conditions was thus largely unique, whereas the two temporal sources shared explained variance.

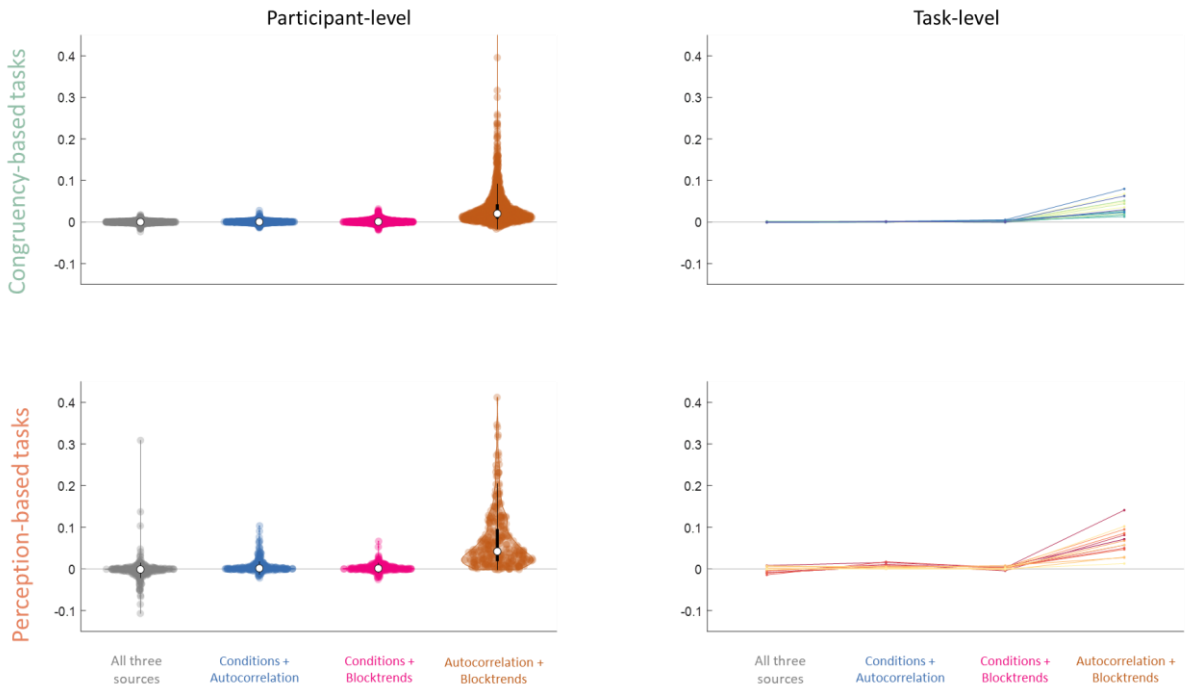

Figure 4. Variance explained commonly by different sources: experimental conditions plus autocorrelational (blue), experimental conditions plus blockwise trends (pink), autocorrelation plus blockwise trends (brown), and all three combined (grey), shown for the congruency-based (top) and the perception-based (bottom) tasks. The communalities are shown both on the participant-level (left, with each dot representing one RT series) and task-level (right), with each dot representing one task. The communalities between autocorrelation and blockwise trends are above zero, indicating an overlap of explained variance. The other three distributions are near zero, indicating negligible overlap.

Control analyses confirm that our results are robust

We conducted several control analyses to inquire whether the above results are robust to choices we had made during data analysis. First, we assessed the influence of different outlier exclusion criteria and commonly applied transformations of RT. Second, we verified that task-irrelevant exogenous elements in the design (e.g., basic stimulus characteristics or inter-trial interval durations) contribute very little to the overall RT variance. Finally, the main analyses were rerun after excluding datasets for which the predictors showed signs of severe multicollinearity. None of these aspects affected the conclusions we have presented: their numerical influences were small. We report these analyses in the Supplementary Materials.

Discussion

We systematically quantified the variance in trial-to-trial RTs explained by experimental conditions and short- and long-range temporal dependencies systematically across a sample of congruency- and perception-based tasks. We focused on studies that are representative of their respective fields; the proportions of explained variance were similar across the two task sets. Although the experimental manipulations in these tasks typically induce robust differences between conditions on the level of averaged single subject and group data, they did not explain more variance than temporal dependencies such as autocorrelation and blockwise trends, which are traditionally considered nuisance. In addition, there was no overlap of the variance explained by experimental conditions and temporal dependencies. Hence, while RTs may change systematically over time, RT differences between conditions are stable. Perhaps most strikingly, our results show that the largest part of within-subject variability remains unexplained by the sources analysed in the present work.

We analysed data from two types of tasks that are often used in experimental psychology and cognitive neuroscience: congruency-based tasks and psychophysical perception tasks. Some have argued that psychophysical tasks are

particularly suited for inducing robust effects across participants (Smith & Little, 2018), given the frequent use of individually-calibrated stimuli (which enhances the condition effect at the individual level) and the collection of small but well-trained samples (which reduces the error variance compared to testing naïve participants). In contrast, most congruency-based tasks employ fixed group designs and rely on larger, untrained participant samples. These differences are also reflected in the datasets analysed here: congruency-based tasks included more participants, while perception-based tasks featured more trials and blocks. In total, seven studies used individually calibrated stimuli, but their variance patterns were not different from other tasks in any obvious way (see Table 3). However, we do not the means to systematically compare the two types of tasks, and only conclude that our overall conclusions hold up across both.

Experimental effects versus intra-individual variability

Typically, significant differences between experimental conditions are interpreted in the form of *'responses are faster in condition A than in condition B'*. Such interpretations emphasise the *direction* (not the magnitude; also see Rouder & Haaf, 2021) of the difference between condition-wise *summary statistics (such as means and medians)* that are usually further *summarised across participants*. In this form, many experimental effects, including those analysed in the current study, are considered to be highly robust even if the magnitude of a condition-difference may be small (Rouder et al., 2019; Rouder & Haaf, 2018).

Yet our results show that even if the group-wise effect of an experimental manipulation is replicable, the moment-to-moment variability of an individual participant's responses remains largely unpredictable. For example, a well-known cognitive congruency effect (the Stroop effect) was replicated in each of 20 independent participant pools in the cross-laboratory experiment "Many Labs 3" (Ebersole et al., 2016). If we were to test a naïve participant on this task, we could predict that their (average) behaviour would be faster in the congruent compared to the incongruent condition. However, as shown by our analysis, our ability to predict individual RTs remains poor even for this particular task. Hence, the experimental

conditions in typical neurocognitive tasks have low explanatory power for RT at the single-trial level.

Temporal dependency in variability

Short- and long-range temporal dependencies explained more variance than the experimental conditions. Still their total contribution to explained variance low, implying that knowledge of the precise temporal patterns of variability (e.g., the strength of autocorrelation) provides only poor prediction of the individual RTs.

For practical reasons we limited the analysis on specific (first and second-order) forms of temporal structures, though some studies have described higher-order structures in RTs. For example, one line of research has described long-range or scale-free patterns in behaviour (e.g., Gilden, 2001; Kello et al, 2007; Thornton & Gilden, 2005; Van Orden et al., 2003). Often, such structure has been quantified using frequency analysis (Box et al., 2016) and some studies have claimed that long-range structures explain “a fair fraction” of the total variance, and in some cases more than the experimental conditions (Gilden, 2001, p. 54). These analysis methods come with various controversies, and the explained variance cannot be attributed to defined timescales, which limits its interpretability (see Wagenmakers et al., 2004 for a comprehensive overview; also see Farrell et al., 2006). In addition, entering such structures into an analysis of shared and unique variances is not straightforward. As such, it remains open whether higher-order temporal structures explain more variance than the autocorrelations and block-wise trends investigated here.

Generalisability of findings

For our study, we analysed data from studies on cognitive control and sensory perception, using tasks that are well representative of their respective research fields. Proportions of explained variance were highly similar across congruency- and perception-based tasks. Whether our findings generalise to other types of tasks and disciplines remains an empirical question. However, congruency- and perception-based paradigms tend to produce condition differences in RT on the group level, and both typically include relatively high trial numbers to minimise measurement error

compared to other fields (e.g., motor control, memory), and are often associated with error rates that are either low or fixed at the group level (e.g., by using staircase procedures). It seems unlikely we would find larger proportions of explained variance by experimental manipulations in tasks that do not share these characteristics. Furthermore, the potential reasons for why our behaviour may be variable seem largely universal (see section *Other predictors of trial-to-trial fluctuations* below). Overall, the low proportion of explained variance may thus be a general feature of neurocognitive tasks. Similar conclusions have been drawn in animal work (Musall et al., 2019). This may reflect that the ongoing experimental task is only a small part of the plethora of activity the brain is processing at each moment in time, even in highly controlled laboratory environments.

Our analyses only include tasks that involve manual button presses. RT produced by other modalities are quantitatively different from button presses – e.g., RT latencies from button presses are longer than those from saccadic eye movements). More importantly, they can be *qualitatively* different. For example, in rapid action selection tasks, manual RT had longer and more variable non-decision times – reflecting sensory processing and motor output – compared to saccadic RT (Bompas et al., 2017). If different types of responses are qualitatively different, we cannot easily speculate if the specific proportions of explained variance found in the current study would generalise to trial-to-trial RT from other output modalities. Still, saccadic responses are also known to be highly variable (Carpenter, 1999; Noorani & Carpenter, 2016), and it may be fair to assume that large proportions of this variability would be unrelated to the task.

It is possible that temporal predictability is higher in sensorimotor actions other than the ones we scrutinized in the present study, particularly in tasks without experimental conditions such as tapping to a metronome (see Perquin et al., 2023 for an overview of autocorrelations in RT series from various tasks with and without experimental conditions). However, even in these tasks without experimental conditions, the largest proportion of the RT variance remained unexplained – meaning the trial-to-trial responses were still largely unpredictable.

Other predictors of trial-to-trial fluctuations

Our results show that experimental conditions and temporal dependencies in typical (neuro-)cognitive tasks have low predictive power of trial-to-trial fluctuations in RT. Of course there are other potential sources of trial-to-trial fluctuations that we have not analysed – with the most obvious being of endogenous nature. In the following we discuss two research lines that have investigated potential endogenous contributions to fluctuations in behaviour.

Predicting behavioural fluctuations from attentional state

One line of research explains fluctuations in performance as a result of changes in attentional state – e.g., "I was slow to respond to that other car *because* I was not paying attention". If this is view was correct, attentional states would be one avenue for predicting upcoming responses (e.g., Baldwin et al., 2017). On the one hand, attention may refer to a global state, relating to states as arousal or motivation. Indeed, when participants report to be attentionally off-task (e.g., mind wandering, drowsiness), their average RT variability in trials just before this report is higher compared to when they report to be on-task (Anderson et al., 2021; Laflamme et al., 2018; Seli et al., 2013; Thomson et al., 2014). However, effect sizes tend to be small: fluctuations in attentional state reports can typically only explain ~2-7% of the total trial-to-trial RT variability – though these reports appear to explain more variance in accuracy (Kane et al., 2021). Furthermore, subjective reports are typically measured retrospectively (e.g., "what was your attentional state just before this question appeared?"), but *upcoming* trial-to-trial variability as well as slow and incorrect responses seem to be consciously inaccessible (Perquin et al., 2020), meaning that metacognitive states likely have little to no predictive power.

On the other hand, attention may refer to the more specific mechanism of spatial orienting, which can be experimentally manipulated by introducing attentional cues and increasing predictability of the stimulus – though note that : spatial attention can also vary from trial to trial due to changes in arousal (see Renart & Machens, 2014; Roelfsema 2004). Attentional cues can decrease variability in behaviour and brain activity (Azari et al., 2009; Cohen & Maunsell, 2009; 2010; Ledberg et al., 2012). Likewise though, this effect appears likewise stronger on accuracy than on RT – for example, Azari et al. (2009) found that valid cues increased accuracy compared

to invalid cues, but did not significantly affect RT. Overall, while attentional state is consistently associated with behavioural variability, it is unlikely to explain large proportions of the trial-to-trial fluctuations in RT.

Predicting behavioural fluctuations from neuroimaging data

Variability is present throughout the nervous system from phenomena such as synaptic transmission to cross-network connectivity (for comprehensive reviews, see Ermentrout et al., 2008; Faisal et al., 2008; Garret et al., 2013; Renart & Machens, 2014; Waschke et al., 2021), and is largely independent from the task at hand (Musall et al., 2019). Variability in neural activity prior to registration of a stimulus has been associated with fluctuations in subsequent actions in response to that stimulus across human and animal studies (e.g., Cohen & Maunsell, 2009; Everling et al., 1997; Parto Dezfouli et al., 2018; Supèr et al., 2003; Womelsdorf et al., 2005; Zhang et al., 2008). Correlations between fluctuations in behaviour and brain state have been found across multiple time scales, from ultra-slow (Monto et al., 2008; Weissman et al., 2006) to alpha, beta, and gamma fluctuations (e.g., Bompas et al., 2015; Gonzalez Andino et al., 2005; Hamm et al., 2010; Perfetti et al., 2011). These fluctuations may influence the encoding of sensory stimuli, as evidenced by electroencephalogram (Iemi et al., 2019) and voltage imaging data (Davis et al., 2020; Liu et al., 2022). Oscillatory phase may also play a role (e.g., Busch et al., 2009; Schroeder & Lakatos, 2009; VanRullen, 2016; but for negative findings, see Benwell et al., 2017; Bompas et al., 2015: Ruzzoli et al., 2019). Functional connectivity within and between task, sensory, and default networks also contributes to behavioural variability (e.g., Thompson et al., 2013; Zuberer et al., 2021). Furthermore, fluctuations in behaviour have been associated with other biological processes such as heart beat (e.g., Park et al., 2014; Salomon et al., 2016), respiration (e.g., Johannknecht & Kayser, 2022), and stomach activity (e.g., Rebollo & Tallon-Baudry, 2022; Richter et al., 2017).

Collectively, this make for a very heterogeneous body of work relying on diverse paradigms, analysis methods, and time scale. However, most studies have not reported which proportion of the total variance is explained by the respective source of interest, and endogenous and exogenous sources of variability are

commonly conflated. Studies that do report proportions of explained variance point to low effect sizes: 1-4% of endogenous saccadic RT variability could be explained by oscillatory power across the task-network (Bompas et al., 2015), while total cortical transmission times across task-networks could explain on average 8% of simple RT variability (Paraskevopoulou et al., 2021). It is thus unlikely that there is either a single process or a small number of processes that will explain a large proportion of behavioural variability.

Perspectives for future research

A comprehensive understanding of human behaviour as such requires an understanding of the contributing endogenous fluctuations (see Evans et al., 2020; Uddin, 2020). Several approaches may be beneficial for addressing this question.

First, endogenous and exogenous variability are often not fully separated; any time-varying task-element (e.g., interleaved conditions, inter-trial intervals, breaks) can potentially affect behaviour. When the interest lies on endogenous – i.e., spontaneous – fluctuations, it is therefore important to minimise exogenous elements. This can for example be achieved by using highly repetitive tasks, such as tapping to a fixed tone or rapid action selection tasks that include easily perceivable stimuli and simple actions. When exogenous factors are still present, they will first need to be removed from the trial-to-trial fluctuations prior to data analysis (e.g., Benwell et al., 2018; Bompas et al., 2015).

Furthermore, multi-modal measurements that concurrently assess neural and bodily signals will be central to identifying which of the many possible neural and bodily processes. An important aspect for the identification of variance sources will be that studies routinely report the proportion that each source explains of the total variance on the single trial level. This requires statistical approaches that focus on single trial data rather than summary statistics, and analyse RT as a continuous rather than categorical (e.g., median split) variable.

Both behavioural variability such as the variance across an entire session (Hultsch et al., 2002; Hultsch et al., 2000; Perquin & Bompas, 2019; Perquin et al., 2022; Saville et al., 2011; 2012) as well as temporal dependencies in entire RT series

(Perquin et al., 2023) exhibit considerable stability across time and are thus trait-like. This makes them well-suited for research about individual differences. Various neuropsychiatric diseases have already been associated with increased variability compared to healthy populations, such as ADHD (Kofler et al., 2013; Tamm et al., 2012), Alzheimer's Disease (Tales et al., 2012; Tse et al., 2010), as well as schizophrenia, depression, and borderline disorder (Kaiser et al., 2008; also see Dinstein et al., 2013). Furthermore, recent work has suggested that neural activity associated with experimental factors is highly consistent across participants, but that neural activity associated with fluctuations in task performance has high inter-subject variability, but is stable within individuals over time (Nakuci et al., 2022). These findings suggest that neural fluctuations relating to performance could in itself be an individual trait, though their reliability over time and contexts remains an open question.

More complex computational models capture variability in latent variables. For example, accumulation models (e.g., Bogacz et al., 2006; Ratcliff et al., 2016) identify a drift rate of evidence accumulation for the ongoing decision and a threshold at which decisions are committed to. These types of models have been successful at simulating RT distributions and capturing the relationship between RT and accuracy, and may even be restricted with neuroimaging data (e.g., Turner et al., 2013; 2016). However, their contribution to understanding trial-to-trial fluctuations is limited, because a) they include noise parameters agnostically fitted solely for the purpose of computational tractability, b) they posit, by definition, that RT series are random over time, and c) they cannot, for this reason, predict a single trial's random walk or evidence accumulation (also see Evans et al., 2020; Evans & Wagenmakers, 2019). One avenue to understanding trial-to-trial fluctuations might be to expand such models, for example, by incorporating temporal dependencies and implementing single-trial estimates of latent variables. We note that accumulation models may implement within-trial (drift rate) and between-trial (e.g., between-trial standard deviation of drift rate) variability, representing fast fluctuations in accumulation within single trials and slower fluctuations in global processes across trials respectively. However, our current analyses do not allow for a distinction of within- and between-trial variability, which would require either neural recordings (e.g., Steinemann et al., 2022) or specific experimental manipulations (e.g., Ratcliff et al., 2018; Ritz &

Shenhav, 2022). Overall, the question to which convenience noise parameters relate to neurocognitive processes remains largely open (Evans et al., 2020; Evans & Wagenmakers, 2019).

Finally, we would like to note that while our analysis indicates that the variance explained by experimental conditions and temporal dependencies are unique, this independence does not provide a rationale for refraining from the inclusion of temporal dependencies in statistical analysis of experimental effects. Incorporating temporal dependencies can still reduce the error variance, and can as such be beneficial for statistical detection of the experimental effect (e.g., Baayen & Milin, 2010; Fründ et al., 2014).

Conclusion

Experiments are a key tool for identifying factors that influence neural processing and behaviour when we aggregate over trials and/or individuals, but they predict only a fraction of intra-individual variability. Endogenous sources likely contribute a much higher proportion to moment-to-moment fluctuations than exogenous influences. In laboratory-derived behaviour data, endogenous or unexplained variability often carries the negative connotation of simply being measurement error.

However, variability may be an intrinsic and important feature of our biological system (Faisal et al., 2008; Garrett et al., 2013). Random variability has been highlighted as a possible means to facilitate creative, flexible, and strategic behaviour and even free will, as randomness in behaviour prevents stereotypy and monotony (Carpenter, 1999; Renart & Machens, 2014). Ultimately, unpredictable variability might be advantageous in contexts in which perpetuation is unwarranted, be it fleeing from a predator, exploring the environment, deciding between similar options, motor learning, or curiosity (e.g., Briffa, 2013; Chang et al., 2017; Dinstein et al., 2013; Shahan & Chase, 2002; Sternad, 2018). The larger empirical question is therefore to what extent trial-to-trial variability is predictable. scrutinised all possible endogenous

sources of variability, it is possible that some proportion of variability is truly random and thus evade precise trial-to-trial prediction.

Materials and methods

Methods were the same for the congruency-based and the perception-based tasks, and are described for both below. Note that the labels ‘congruency-based’ and ‘perception-based’ are used as practical way to refer to the main field and theoretical interest of the task, not to a fundamental difference of task type.

Selection of datasets

We collected datasets from previously published studies, both from publicly available sources (e.g., OSF, github) and from our own work. We applied the following criteria to select datasets:

1. The experimental conditions had to be implemented in a within-subject design as a necessary condition for studying within-subject variance.
2. Experimental conditions were presented (pseudo-) randomly across trials (rather than in a blockwise manner), allowing us to investigate the relative contributions of the sequential and naturally-occuring temporal effects in experimental condition.
3. The task was was not explicitly intended to affect participants’ performance over time; thus, for instance, learning or fatigue-inducing studies would not meet this criterion. Such paradigms induce temporal dependencies that would confound experimental and temporal aspects as defined in our study.
4. The task consisted of either one or two independent experimental conditions of interest to facilitate analysis, as each additional condition would result in an increasingly disproportional amount of predictors for a GLM. Capturing two experimental conditions A and B in our model requires six predictors (*A, B, A*B,* on the current and previous trial), while three experimental conditions would require fourteen (*A, B, C, A*B, A*C, B*C, A*B*C*), and four experimental conditions would require 28.

5. The dataset featured at least 15 participants to obtain a reasonable estimate of the explained variance at the task-level.
6. The task consisted of minimally 20 trials for each predictor to ensure sufficient statistical power for within-subject GLMs.
7. The dataset includeed the raw (trial-to-trial) data and, for each trial, the RT, accuracy, experimental condition(s), trial, and block number (or, if missing, can be inferred from the original paper), and
8. RT were measured using manual button presses, the most commonly used response measure.

Note that both for data selection and data analysis purposes, we use the term ‘experimental condition’ to refer to those manipulations that were of interest in the (statistical) comparison of the task at hand. For instance, in a Stroop task, experimenters use different words and colours for the stimuli, but the interest lies in the difference between congruent, neutral, and incongruent trials independently of the specific word-colour combination. As such, this task has 1 condition (‘congruency’) that we use throughout the main analyses, as this is the driving source of experimentally induced variance. We will address the effect of other endogenous elements in the *Control analyses* (section *Additional sources of variance*).

Selected datasets

Congruency-based datasets

Sixteen datasets were selected for analysis (see Table 2 for an overview, and the Supplementary Materials for a full description). Of these, eleven were collected through a previous large-scale reanalysis of congruency-based tasks (Rouder, Kumat & Haaf, 2019), an additional three through the Confidence Database on OSF (Rahnev et al., 2019), and two were already in possession by the first author for another study (Perquin et al., 2023). We note that for these last two tasks, the autocorrelation in RT has been previously reported alongside other temporal structure measures. All analysed datasets have been included in the current study.

Perception-based tasks

Fourteen tasks were selected for analysis (see Table 3 for an overview, and the Supplementary Materials for a full description). Of these, six came from our own lab, one was found through the same large-scale reanalysis as above (Rouder et al., 2019), and an additional eight were found in the Confidence Database on OSF (Rahnev et al., 2020). One additional analysed dataset has not been included in the current study, as this concerned a simple detection task with a high number of anticipations, and all participants would have too little trials for our purposes after data exclusion.

Table 2. Overview of selected congruency-based datasets, showing the dataset name (dataset), total number of participants with complete data sets (# ppt), number of excluded participants in analysis based on % excluded trials (# excluded; see Methods above), the experimental condition(s) of interest with the number of levels in brackets (condition), the perceptual type of the stimulus (stimulus), the total number of blocks (blocks), the number of trials per block (trials/block) and per experiment (total trial #), the number of independent factors to predict RT (# predictors) for each participant, the original study in which the data was first published, and the original exclusion rules for RT outliers in the original study.

Dataset	**# ppt**	**# excluded**	**condition (# levels)**	**stimulus**	**blocks**	**trials/ block**	**Total trial #**	**# predictors**	**Original paper**	**Original exclusion rules**
1. Stroop	38	1	congruency (3)	visual	7	72	504	11	Pratte et al. (2010)	<200ms, >2000ms
2. Simon	38	0	congruency (3)	visual	7	72	504	11	Pratte et al. (2010)	<200ms, >2000ms
3. Flanker	107	4	congruency (3)	visual	5	144	720	9	Hedge et al. (2019)	<100ms, >3SD+median
4. Stroop	107	1	congruency (3)	visual	5	144	720	9	Hedge et al. (2019)	<100ms, >3SD+median
5. Digit distance	54	3	difficulty (3)	visual	6	60	360	10	Rouder et al. (2005)	<250ms, >2000ms

6. Flanker Arrow (young participants)	120	10	congruency (3)	visual	4	74	296	8	Rey-Mermet et al. (2018)	<250ms, >2.5SD+mean
7. Flanker Arrow (older participants)	149	10	congruency (3)	visual	4	74	296	8	Rey-Mermet et al. (2018)	<250ms, >2.5SD+mean
8. Flanker Letter (young)	120	13	congruency (3)	visual	4	74	296	8	Rey-Mermet et al. (2018)	<250ms, >2.5SD+mean
9. Flanker Letter (old)	148	18	congruency (3)	visual	4	74	296	8	Rey-Mermet et al. (2018)	<250ms, >2.5SD+mean
10. Stroop Colour (young)	120	5	congruency (3)	visual	4	74	296	8	Rey-Mermet et al. (2018)	<250ms, >2.5SD+mean
11. Stroop Colour (old)	149	16	congruency (3)	visual	4	74	296	8	Rey-Mermet et al. (2018)	<250ms, >2.5SD+mean
12. Stroop Number (young)	119	2	congruency (3)	visual	4	74	296	8	Rey-Mermet et al. (2018)	<250ms, >2.5SD+mean
13. Stroop Number (old)	147	17	congruency (3)	visual	4	74	296	8	Rey-Mermet et al. (2018)	<250ms, >2.5SD+mean

14. Priming congruency	31	4	congruency (2)	visual	8	80	640	12	Desender et al. (2016)	N/A
15. Priming congruency	86	10	congruency (2)	visual	8	60	420	10	Desender et al. (2014)	none
16. Priming congruency	30	4	congruency (3)	visual	6	144	846	6	Teuchies et al. (2019)	>1500ms

Table 3. Overview of selected perception-based datasets. Same conventions as Table 2.

Dataset	**# ppt**	**# excluded**	**condition (# levels)**	**stimulus**	**blocks**	**trials/ block**	**Total trial #**	**# predictors**	**Original paper**	**Original exclusion rules**
1. Grating orientation discrimination	57	5	difficulty (3) x direction (2)	visual	9	80	17	17	Rouder et al. (2010)	<200ms, >5000ms
2. Random dots direction discrimination (young)	18	0	congruency (2) x coherence (adaptive; R)	Visual + auditory	5	240	13	13	Kayser & Kayser (2018)	<300ms, >1200ms
3. Random dots direction discrimination (old)	23	0	congruency (2) x coherence (adaptive; R)	Visual + auditory	3	240	11	11	Park, Nannt & Kayser (2020)	<300ms, >1200ms

4. Frequency discrimination	16	0	Frequency (7) x delay (6)	Auditory	4	168	12	12	Kayser et al. (2016)	N/A
5. Intensity discrimination	16	0	Intensity (7) x delay (6)	Auditory	Subject-dependent, ranging 3-5	168	11-13	11-13	Kayser et al. (2016)	N/A
6. Location discrimination	30	0	Modality of stimulus (3) x direction (2)	Visual, auditory, or visuo-auditory	4	Subject-dependent, 239 or 215	12	11-13	Kayser (unpublished pilot data)	N/A
7. Two choice noisy target detection	30	7	Location (2)	visual	10	100	14	14	Maniscalco et al. (2017)	N/A
8. Two choice noisy target detection	41	4	Location (2) x coherence (3)	visual	5	102	13	13	Maniscalco et al. (2017)	N/A
9. Grating orientation discrimination	15	1	Contrast (2)	visual	2	160	6	6	Samaha et al. (2016)	<3SD+mean, >3SD+mean
10. Grating orientation discrimination	20	0	Contrast (adaptive; R)	visual	3	100	7	7	Samaha et al. (2017)	<200ms, highest 5%
11. Grating contrast discrimination	19	0	Contrast (adaptive; R)	visual	3	100	7	7	Samaha et al. (2017)	<200ms, highest 5%

12. Short term memory of grating orientation	20	5	Contrast (adaptive; R)	visual	3	100	7	7	Samaha et al. (2017)	<200ms, highest 5%
13. Colour judgment	24	9	Combination of mean and variance of colour (4)	visual	8	Subject-dependent, 60 or 64	12	12	Desender et al. (2019)	N/A
14. Facial emotion recognition	21	1	Emotion category (2)	visual	2	200	6	6	Johannknecht & Kayser (2022)	< 200 ms >3SD+mean of log(RT)

Data analysis

Fitting General Linear Models

Full model. To quantify the total explained within-subject variance, we fit general linear models (GLMs) for each participant on RT as dependent variable, using the *fitglm* function in Matlab 9 (Mathworks, 2021) with an Iterative Reweighted least squares algorhitm. All GLMs included the following predictors:

1. experimental condition(s) in the current trial,
   1b. if the design included two experimental conditions: the interaction between experimental conditions in the current trial,
2. experimental condition(s) of the previous trial,
   2b. if the design included two experimental conditions: the interaction between experimental conditions in the previous trial,
3. RT of the previous trial,
4. RT of two trials ago,
5. the linear trend in trial number, separately for each block, and
6. the quadratic trend in trial number, seperately for each block.

Points 1 and 2 represent the experimental conditions, 3 and 4 the autocorrelation, and 5 and 6 the blockwise trends.

From the GLM fits, we extracted the amount of explained variance (R^2_{abc}), calculated as:

$$R^2_{abc} = \frac{Sum\ of\ Squares_{residual}}{Sum\ of\ Squares_{total}}$$

R^2_{abc} refers to the total amount of trial-to-trial variance in RT explained by all predictors– i.e., the combination of the experimental conditions (c), autocorrelation (a), and blockwise linear trend (b) all together. Hence, the amount of unexplained variance can be calculated by 1 - R^2_{abc}.

As R^2_{abc} can be inflated due biases arising from limited data, we implemented a correction. This was done by randomly shuffling the RT series and fitting the GLMs

on these shuffled series 100 times, and calculating the average explained variance across these 100 iterations – resulting in an estimate of explained variance by noise. This estimate was subtracted from $R^2_{abc.}$ Note that these corrected variance estimates can in princinple be negative, whith values near zero indicating that the variance explained in the actual data is comparable to an amount of variance explained by chance.

Fitting each source of variability separately. Aside from the total amount of explained variance, we were also interested in how much variance each of the three sources – experimental conditions, autocorrelation, and blockwise trends – could explain by itself. We fitted separate GLMs by removing all other terms from the overall regression equation, and extracted explained variance for each – R^2_c, R^2_a, and R^2_b respectively. These three estimates were corrected by noise in the same manner as above.

These R^2 values reflect the variance each source explains in total while not controlling for the variance it shares with the other two sources. The variance explained by the full model (R^2_{abc}) can therefore be lower than the sum of R^2_c, R^2_a, and R^2_b. This is illustrated in Figure 2C: part of the explained variance may overlap between sources. To quantify the amount of variance that is *uniquely* explained by each source (i.e., the size of the non-overlapping parts of the circles), we subsequently used variance partitioning analysis (Borcard, et al., 1992).

Partitioning variance

Unique explained variance. To partition the variance, we first fitted each two-way combination of the three sources (experimental conditions plus autocorrelation, experimental conditions plus blockwise trends, and autocorrelation plus blockwise trends) and extracted their explained variance: R^2_{ac}, R^2_{bc}, and R^2_{ab} respectively. These estimates were again corrected for noise. Next, to quantify the unique explained variance for each source, the R^2 from the other two sources combined was subtracted from the total amount of explained variance by all three sources together. For example, we calculated the unique explained variance by the experimental conditions ($R^2_{c.ab}$) as:

$$R^2_{c.ab} = R^2_{abc} - R^2_{ab}$$

Communalities. Besides the unique explained variance, variance partitioning offers a quantification of the amount of shared variance (i.e., the overlapping parts of the circle; Figure 2D). For example, the communality C_{ab} between autocorrelation and blockwise trends (overlap in green and orange circle in Figure 2D) was calculated as:

$$C_{ab} = R^2_{bc} + R^2_{ac} - R^2_{c} - R^2_{abc}$$

and the communalities C_{abc} between all three sources as:

$$C_{abc} = R^2_{a} + R^2_{b} + R^2_{c} - R^2_{ac} - R^2_{ab} - R^2_{bc} + R^2_{abc}$$

Note that theoretically communalities cannot be <0. However, for the noise-corrected variance estimates used here they can be, again with values near zero indicating no common variance.

Data availability

The datasets from our own collected experiments will be made available on OSF alongside the analysis code upon publication. We will provide links to the openly available datasets from other researchers.

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Supplementary Materials A

Description of congruency-based datasets

1-2. Thirty-eight participants performed a Stroop and a Simon task (Pratte et al., 2010). In the Stroop task, they had to name the colour of the word. The main condition was the written word, which could be congruent, incongruent, or neutral. In the Simon task, participants were shown a red or green square, which they had to press a response button with their right- or left-hand respectively.

The main condition of interest is the side of the presented stimulus (left or right of a central fixation), which could be congruent (e.g., red square presented on the right side of the screen) or incongruent (e.g., red square presented on the left side) to their response hand. For both tasks, participants completed 7 blocks of 74 trials, which were presented with a fixed ITI (700 ms).

3-4. Hundred-and-seven participants took part in two sessions (three weeks apart) in a laboratory experiment, in which they completed the Eriksen Flanker, Stroop, Go/No-Go, and Stop-signal (Hedge et al., 2019). We analysed the data series from the Eriksen Flanker and Stroop tasks, using only the first session.

In the Eriksen Flanker task, participants had to discriminate the direction of a central arrow (left- or rightwards). The main condition for our analysis is the congruency of the four surrounding flankers to the target (congruent, incongruent, or neutral). In the Stroop task, participants had to name the colour of a word. The main condition was the congruency of the written word to the colour (congruent, incongruent, or neutral). For both tasks, participants completed 5 blocks of 144 trials, which were presented with a fixed ITI (1000 ms).

5. Fifty-four participants performed a digit distance task, in which they had respond whether the presented digit was higher or lower than 5 (Rouder et al., 2005). The

main condition of interest is the difficulty (distance from 5), which could be easy (2 or 8), medium (3 or 7), or hard (4 or 6). Participants performed 6 blocks of 60 trials, presented at a fixed ITI of 400 ms, during which they received auditory feedback on their accuracy.

6-13. 130 young (18-28 years) and 159 older (64-76 years) participants took part in a two-day experiment involving 11 different neurocognitive tasks. We used the data from two Stroop (Colour and Number) and two Flanker (Arrow and Letter) tasks (Rey-Mermet et al., 2018). Data from the two age groups were analysed separately – thus resulting in 8 separate tasks for our analyses. As per the original paper, participants with high scores on dementia and depression screening questionnaires (Mini-Mental State, Beck Depression Inventory II, Geriatric Depression Scale) were excluded (17 participants), and another two participants were excluded due to experimenter error in the testing session.

In the Colour Stroop task, participants had to name the colour of the word while ignoring the written word, while in the Number Stroop task, they had to respond how many digits were shown, while ignoring the value of the digits. In the Arrow Flanker task, participants had to discriminate the direction of the arrow, while ignoring flankers. In the Letter Flanker task, they had to respond whether the central letter was a vowel (‘S’ or ‘H’) or a consonant (‘E’ or ‘U’), while ignoring the surrounding congruent (e.g., central vowel with vowels) and incongruent (e.g., central vowel with consonants) flankers.

For each task, the main condition is congruency (congruent or incongruent). Participants completed 4 blocks of 74 trials for each task, presented at a fixed ITI of 1000 ms, during which they were presented with feedback on response accuracy. There was a response deadline of 1900 ms after stimulus onset. All participants were presented with the same stimulus sequence, which contained no complete stimulus repetitions.

14. Thirty-one participants performed a priming congruency task, in which they had to discriminate the left- or rightwards direction of an arrow (Desender et al., 2016). Prior

to stimulus onset, a smaller priming arrow was shown for 34 ms, which fitted into the contour of the stimulus arrow (and hence was invisible to the participant), followed by a black screen for 34 ms. If a response was made within 3000 ms, participants were subsequently asked to rate the confidence in their response. The main condition is the congruency of the prime (congruent or incongruent). Participants completed 8 blocks of 80 trials, presented at a fixed ITI of 800 ms.

15. Eighty-six participants performed a priming congruency task (Desender et al., 2014). On each trial, they were first shown a priming arrow for 23 ms (pointed left- or rightwards), which was followed by two masks and a blank screen of 23 ms each. Next, they were presented with a stimulus arrow (160 ms), and were asked to discriminate the direction of the arrow (left or right). The main condition is the congruency of the prime (congruent or incongruent). Participants completed 8 blocks of 60 trials. The ITI was self-paced, and there was a response deadline of 3000 ms after stimulus onset.

16. Thirty participants performed a priming congruency task (Teuchies et al., 2019), in which they had to discriminate the direction of an arrow (left or right), which was shown for 250 ms. Prior to stimulus onset, they were presented with a prime arrow and black screen, both for 17 ms. The prime arrow fitted into the contour of the stimulus arrow and was hence masked. Afterwards, they were asked to rate the confidence in their response.

The main condition is the congruency of the prime (congruent, incongruent, or neutral). Participants completed 6 blocks of 144 trials. The ITI was variable (ranged 1000–5250 ms), and there was a response deadline of 1500 ms after stimulus onset.

Description of perception-based datasets

1. Fifty-eight participants performed an orientation discrimination task, in which they had to respond whether a grating was oriented left- or rightwards (Rouder et al.,

2010). The main condition is the difficulty (tilt of the orientation), which could be easy, medium, or difficult (~4°, 2°, and 1.5° respectively). Participants completed 9 blocks of 80 trials, which were presented with a fixed ITI (1000 ms), during which they received auditory feedback on their accuracy.

2. Eighteen participants performed a multisensory perception task, in which they had to discriminate the left- or rightwards motion of moving dots (Kayser & Kayser, 2018). An auditory cue was played simultaneously, which could either be congruent or incongruent to the visual information. The coherence of the visual motion (i.e., percentage of dots moving in one direction) could take on four different values (i.e., difficulty levels), which were participant-depended and based on a prior calibration, and were adjusted every 35 trials based on the performance.

The main conditions are the coherence of the visual motion (total number of percentages is participant-depended) and the audio-visual congruency. All participants performed 5 blocks of 240 trials, except one participant who only performed 4 blocks (960 trials). The stimulus was presented for max 1200 ms (or until response), with a variable trial onset (700-1000 ms) and variable ITI (1500-2000 ms).

3. Twenty-three older participants (aged 62-82) performed the same multisensory perception task as in [2] above (Park, Nannt & Kayser, 2020). Likewise, the main conditions are the coherence of the visual motion (total number of percentages is participant-depended) and the audio-visual congruency. All participants performed 3 blocks of 240 trials.

4-5. Sixteen participants performed two separate auditory discrimination tasks (Kayser et al., 2016). On each trial, they heard two different pure tones presented in background noise. In the frequency task, they were asked which of the tones had the highest frequency. In the intensity task, they were asked which tone was the loudest. Note that the first tone was always fixed (i.e., always the same frequency/loudness), while the second one could vary over seven levels. These levels were participant-

dependent and based on a prior calibration session, with the lowest level being 0 (Hz or dB) for everyone.

The main condition is the difference in intensity or frequency. Trials were presented at a variable interval (1700-2200 ms) and with a variable duration between the two tones (2400-2562 ms). For the intensity task, all participants performed 4 blocks of 168 (= 672) trials, except one participant who performed 3 blocks (504 trials). For the frequency task, 4 participants performed 3 blocks (504 trials), 1 participant performed 5 blocks (840 trials), and 11 participants performed 4 blocks (672 trials).

6. Thirty participants performed a detection task, featuring auditory, visual, and audio-visual targets (unpublished pilot data). The target was presented at the left or the right side, and participants had to detect it. The main condition is stimulus type. All participants completed 4 blocks, with block size being 239 trials for 7 participants (= 956 trials), and 215 trials for the others (860 trials).

7. Thirty participants performed a noisy detection task (Maniscalco et al., 2017). On each trial, they were shown two patches of noise for 33 ms, and were asked which patch contained a target. The target's contrast was fixed and participant-depended (based on a 120-trial calibration). Afterwards, participants rated the confidence in their response. The main condition of interest is the location of the target (left or right). Participants performed 10 blocks of 100 trials, presented at a fixed ITI of 1000 ms.

8. Forty-one participants performed a noisy detection task, with an interleaved memory task (Maniscalco et al., 2017). We analyse the data from the detection task only. On each trial, they were shown two patches of noise for 33 ms, and were asked which patch contained a target. The target's contrast was presented at three different difficulties (participant-depended, based on calibration). Afterwards, participants rated the confidence in their response.

The main conditions are the location (left or right) and the contrast of the target. Participants performed 5 blocks of 102 trials, collected over two days. Trials were presented with a fixed ITI of 1000 ms.

9. Fifteen participants performed an orientation discrimination task (Samaha et al., 2016), in which they had respond whether a grating (shown for 33 ms) was titled left- or rightwards at 45°. The main condition is the difficulty (easy or hard), which related to the noise of the grating, and was participant-depended (based on prior calibration). Participants performed 2 blocks of 160 trials, collected over two days. Trials were presented at a variable ITI (300-500 ms).

10-12. Twenty participants performed three tasks each (Samaha et al., 2017). In the contrast perception task, participants were shown two gratings on each trial, and were asked which grating had the highest contrast. In the orientation discrimination task, participants were also shown two gratings, and had to respond whether their orientations were same or different (25° more tilt). In the visual short-range memory task, participants were shown one target, followed by a 3 s blank screen, and then the second target. Likewise, they had to respond if the orientations were the same or different.

For all tasks, the main condition is the contrast of the stimuli. Participants performed 3 blocks of 100 trials for each task, which were presented at a variable ITI (300-500 ms). Only for the contrast perception task, one participant only completed 2 blocks, and one participant only 1 block – the latter was excluded from analysis on this task. After each trial, participants had to rate the confidence in their response. The contrast was individually determined with a prior calibration and adaptive throughout each task.

13. Twenty-four participants performed a colour judgment task (Desender et al., 2019). On each trial, they were shown 8 coloured dots presented in a circle around a central fixation. Participants had to judge whether the average colour across all dots was more blue or more red. Next, they were asked to rate the confidence in their

response (though half of the participants only were asked for a rating in the even blocks).

The main conditions of interest are the mean and the variance of the colour. Half of the participants performed 8 blocks of 60 (= 420) trials, and half performed 8 blocks of 64 (= 512) trials. Trials were presented with a fixed ITI of 1000 ms, and there was a response deadline of 1500 ms.

14. Twenty-one participants performed an emotion discrimination task, in which they had to respond whether the presented face was angry or happy (Johannknecht & Kayser, 2022). The stimulus face was shown for 100 ms. The main condition is the emotion (angry/happy). Participants performed 2 blocks of 200 trials, with trials being presented with a variable trial onset 400-1000 ms) and ITI (1200-1500 ms).

Supplementary Materials B

Effect of analysis choices

In our main analyses, RT outliers were removed with one common criterion for outlier exclusion across all participants: a lower cut-off of 150 ms and an upper cut-off of 3 SD above the median RT for outlier exclusion. Subsequently, RT were inverse-transformed. Here, we ask how our results are affected by these specific preprocessing choices. Moreover, we compared the result patterns across different choices on transformations of the RT series, specifically comparing inverse, log, or square root transformation, as well as no transformation. We also checked for the effect of outlier exclusion. The RT exclusion method was taken from the original paper if available (reported in Table 2 and 3). Note that some papers only analysed accuracy and therefore did not include an RT exclusion method. For these papers we kept the < 150 ms and > median RT plus 3 SD(RT) cut-off. Again, analyses were run using all four transformation methods (Table B1; bottom). Congruency- and

perception-based tasks were combined for this control analysis, based on the consistent patterns we had observed across both task types.

For each transformation separately, the total and unique explained variance was extracted for each dataset. We obtained qualitatively very similar results across all analysis choices (see Table B1 for the median explained variance across all participants and tasks).

Table B1. Median explained variance across all participants and all tasks for the full model (R^2_{abc}) and the total plus unique explained variance for each of three sources separately under (2 outlier exclusion x 4 data transformations =) 8 different analysis choices. The numerically highest value for each R^2 is shown in bold.

		Full model	Condition		Autocorrelation		Blockwise	
			total	unique	total	unique	total	unique
	inverse	**9.60**	2.61	2.33	**2.98**	**.003**	**4.88**	**2.23**
<150ms and >3SD+median	raw	8.38	**2.75**	2.45	1.97	.001	3.95	2.07
	log	9.07	2.69	2.47	2.55	.002	4.49	2.20
	square root	8.79	**2.75**	**2.52**	2.31	.001	4.22	2.11
	inverse	**9.96**	2.55	2.25	**3.22**	**.004**	**5.08**	**2.25**
Original paper	raw	8.41	2.38	2.16	2.06	.0004	4.12	2.08
	log	9.50	**2.56**	**2.29**	2.69	.003	4.77	2.20
	square root	8.68	2.43	2.16	2.32	-.0001	4.50	2.09

Additional sources of variance

Our analyses were focused on the experimental conditions of interest. However, the analysed tasks contain additional exogenous sources, such as a variable ITI or a redundant visual feature of the stimulus (e.g., the actual direction of the target arrow in the Flanker task). On the group level, the effects of arrow direction are often not statistically different from zero, but for each individual participant, the explained variance will numerically be higher than zero. As a control analysis, we therefore ran

single-subject GLMs to examine if the amount of explained variance substantially increases when taking additional exogenous sources into account.

GLMs were computed for all datasets that included additional exogenous sources that were uncorrelated with the experimental conditions, if made available at their archival source (11 datasets in total across congruency and perception-based tasks). For example, in the Simon task from Pratte et al. (2010), the colour and location of the stimulus varied across the trials independently from the experimental condition. Both of these factors were added to the new GLM. In this particular example, the additional factors explained 1.11% of the total variance.

Table B2 shows an overview of the additional exogenous factors added to the GLM, as well as the original explained variance by the full model (Figure 3 and 5) and the extended model's explained variance. Overall, increases in explained variance were small, with a median increase of 1.32%.

Table B2. Overview of analysed datasets in GLMs featuring additional exogenous sources. Shown are the 11 included task, with the exogenous sources that have been added to the new GLM (and the exogenous sources that could not be included due to non-availability in the datasets, where applicable), with their original and new amount of explained variance (R^2). Increases in explained variance are minimum for most of the datasets.

	Added predictors (levels)	**Not available in dataset**	**Original R^2**	**New R^2**
Congruency-based tasks				
2. Simon task	Colour of stimulus (2); Location of stimulus (2)		11.05	12.16
5. Digit distance	Distance from 5		10.17	10.91
14. Priming congruency	Direction of stimulus (2)		27.61	29.77
15. Priming congruency	Direction of stimulus (2)	Variable ITI	15.39	16.71
16. Priming congruency	Direction of stimulus (2)	Variable ITI	6.99	9.49
Perception-based tasks				
2. Random dots direction discrimination (young)	ITI (R); Pre-trial fixation time (R); Direction of visual stimulus (2); Direction of auditory stimulus (2)		28.92	29.85

3. Random dots direction discrimination (older)	ITI (R); Pre-trial fixation time (R); Direction of visual stimulus (2); Direction of auditory stimulus (2)		17.10	19.78
10. Grating orientation discrimination	Stimulus orientation (2)	Variable ITI	10.50	11.01
11. Grating orientation discrimination	Stimulus orientation (2)	Variable ITI	7.97	10.95
12. Grating contrast discrimination	Stimulus orientation (2)	Variable ITI	8.03	8.63
13. Short term memory of grating orientation	Stimulus orientation (2)	Variable ITI	12.84	15.40

Multicollinearity

As our models feature a large number of predictors, we tested if these predictors met the assumption of absence of multicollinearity. For each participant, the tolerance value and Variance Inflation Factor were calculated for each predictor. There is reason to assume severe multicollinearity for 8 of the 31 datasets, defined as a tolerance > .10 and a VIF > 10, for the experimental predictors for almost all participants. These were tasks that either featured two experimental conditions and/or a stimulus that changes throughout the task (e.g., stimulus contrast adjusting to current performance). We removed these 8 tasks from the dataset and assessed whether the overall result pattern would be affected; such a change of results would imply that our analysis and conclusions are contaminated by predictor multicollinearity. However, the amount of explained variance for the different variability sources was similar with and without the 8 identified tasks (see Table B3), suggesting that multicollinearity did not impact our conclusions.

Table 3B. Median explained variance across all participants for the full model (R^2_{abc}) and the total plus unique explained variance, after excluding the datasets with indications of serious multicollinearity.

Full model	Condition		Autocorrelation		Blockwise	
	total	unique	total	unique	total	unique
8.68	2.41	2.23	2.59	.002	7.10	2.10

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