Shift costs in Reaction Time and Learning are dissociable in modality shifting task

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Abstract

Attentional set shifting has been characterised using accuracy- or performance-based and reaction time–based shift costs across the literature, where "shift cost" is often treated as a unitary construct despite differences in how it is defined and measured. Using a GO/NOGO task with repeated intra- and extra-dimensional shifts between auditory and visual targets, we examined response (accuracy and reaction time, RT) dynamics for cross-modal shifts, using task difficulty to manipulate attentional load prior to shifts. Our prior work using this paradigm demonstrated that increased attentional demands prolong learning (to perform at sustained high accuracy) following modality shifts, raising the question: do RT-based shift costs show a similar sensitivity to task difficulty? The results demonstrated that RT-based shift costs were not increased following difficult tasks, but instead, reflected established sensory modality dominance effects. However, RT dynamics are not independent of learning: longer pre-shift RT predicted higher subsequent learning shift costs, revealing an interaction between processing time (attentional demand) and task difficulty in shaping learning.

Keywords: attentional set shifting; shift cost; sensory dominance

Introduction

Cognitive flexibility is commonly studied using the attentional set-shifting paradigm, in which participants learn to respond based on one task-relevant stimulus dimension and are later required to shift attention to another dimension while the task structure remains unchanged (Brown & Tait, 2015). Such shifts may involve changes in stimulus features, abstract rules, or sensory modality. A robust finding across this literature is the emergence of a shift cost, typically observed as a decline in one or more aspects of performance following the shift.

Shift costs have been quantified using a range of behavioural measures, including mean accuracy, reaction time (RT), and learning-related indices such as trials to criterion (Dias et al., 1996; Heisler et al., 2015; Monsell, 2003; Owen et al., 1991; Rogers & Monsell, 1995). Although these measures are often treated interchangeably, they likely reflect partially distinct underlying processes. RT is commonly interpreted as an index of online processing efficiency and attentional control (Buckhalt, 1991; Posner, 2005), whereas learning-based measures capture the acquisition and consolidation of new stimulus–response contingencies (Luu et al., 2011).

In previous work using the same experimental paradigm, we demonstrated that modality shifts reliably prolong learning, and that this learning shift cost is exacerbated when the pre-shift task imposes high perceptual demands (Postnova et al., 2025). Specifically, tasks requiring finer discrimination led to longer learning times following a modality switch, suggesting that taxed attentional resources influence subsequent contingency learning. Alongside learning rate, RT has frequently been used as a primary index of shift cost in set-shifting studies, as well as to index changes in processing demands in tasks involving shifts between sensory modalities (Monsell, 2003). However, it remains unclear whether RT reflects the same attentional mechanisms as learning-based measures, or whether it is shaped by partly independent constraints, such as modality-specific processing efficiency or inhibitory control.

In particular, shifts between sensory modalities may be asymmetric (Kato & Konishi, 2006; Koch et al., 2020). Previous studies suggest that sensory modalities can differ in their functional dominance for a given task, leading to unequal processing demands when attention must be reallocated (Sandhu & Dyson, 2013). The dominant modality might be specific to the task and demonstrates a distinctive pattern of changes with higher shift cost when switching from dominant to non-dominant modality, as well as carryover effect when returning to previously trained modality (Lukas et al., 2009). RT may therefore be especially sensitive to the direction of a modality shift, reflecting residual inhibition of a previously dominant modality, rather than the difficulty of the task performed prior to the shift. It has also been proposed that shift costs are not necessarily modality-specific but instead could reflect differences in processing time prior to the shift. That is, higher RT prior to the shift can incur higher shift cost, regardless of sensory modalities' shift direction (Roebuck et al., 2019).

The present study focused on RT as an behavioural measure of performance across modality shifts, quantified at the session level. We asked whether session-level RT dynamics mirror the previously observed effects of task difficulty on learning-based shift costs, or whether they instead reflect modality dominance, shift direction, or the average RT-prior-to-the-shift. By directly comparing RT patterns with learning time based shift costs, we aim to determine whether different behavioural measures capture a single underlying attentional mechanism or multiple, partially dissociable processes.

Method

Participants 55 participants were recruited for the study. Six participants were excluded due to data loss caused by technical errors. 11 participants were excluded based on task

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engagement and effectiveness of the attention manipulation (see Performance Control). 13 participants with formal musical education were excluded from the present analyses, as effects of musical training were outside the scope of this study. The final sample consisted of 25 participants (14 female, 10 male, 1 other; M = 27.72 years, SD = 4.47).

The study was conducted in accordance with the Declaration of Helsinki and approved by the University of Helsinki Ethical Review Board in Humanities and Social and Behavioural Sciences (27/2022).

Task and Procedure

Apparatus: The experiment was conducted in a sound-attenuated room with controlled lighting. Stimuli were presented on a monitor (EIZO FlexScan EV2451; 60.5 cm diagonal) and through Sony MDR-7508 headphones. The task was implemented in PsychoPy v2021.2.3 and run on a Lenovo ThinkStation P350 (Windows 10 Pro).

Participants provided informed consent and completed background questionnaires before being introduced to the task. The task required participants to identify a target (GO) stimulus through trial and error. On each trial, one auditory and one visual stimulus were presented simultaneously. Participants were instructed to press a key only in response to the GO stimulus presented.

Stimuli were presented for 1 s, during which responses were registered. Correct responses to GO stimuli were followed by positive feedback, while incorrect responses to NOGO stimuli resulted in negative feedback. No feedback was given when no response was made. A point system was used to sustain engagement across sessions but was not analysed further.

The experiment consisted of one training session followed by eight test sessions (Figure 1). After training, participants' understanding of the task was confirmed verbally before proceeding.

Stimuli

Each session included two auditory stimuli (pure tones) and two visual stimuli (sinusoidal gratings). In each trial, one auditory and one visual stimulus were presented simultaneously, resulting in four possible stimulus combinations. Within a given session, one modality was designated as task-relevant, with one stimulus serving as the GO stimulus and the other as the NOGO stimulus. The remaining modality was task-irrelevant.

Auditory stimuli differed in frequency by approximately one tone, and visual stimuli differed in grating orientation by 30 degrees. Five distinct stimulus sets were used across the experiment to minimise interference between sessions.

Experimental flow

Following training, participants completed two cycles comprising of the following sessions in order: an intra-dimensional shift (IDS), a staircase procedure, an attention manipulation session (AMS), and an extra-dimensional shift

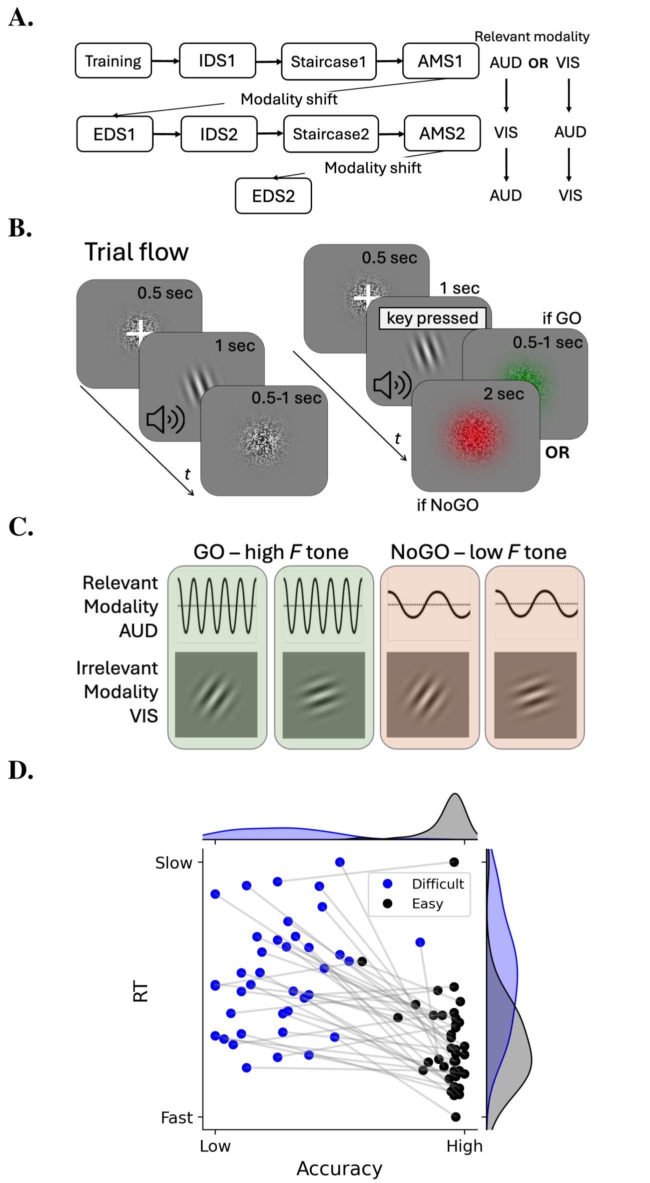


Figure 1: Experiment design at structure, trial, and stimulus levels. **Panel A**: Experimental structure: AUD (auditory) and VIS (visual) indicate the relevant modality for corresponding sessions. Participants were randomly assigned to begin with either the AUD or VIS modality. **Panel B**: trial schematic (visual elements not to scale), with structure: fixation cross, target stimulus, feedback. Three feedback possibilities are shown: no key press, no feedback (left); key press, green light if GO, longer-duration red light if NOGO. **Panel C**: example stimuli under the rule *GO to auditory high 'F' tone* **Panel D**: participant-wise behavioural performance in accuracy (x-axis) and response time (y-axis), for easy (black) vs. difficult (blue) AMS. Axes range from minimum to maximum observed values on scales normalised from 0 to 1. Figures were adapted from Postnova et al. (2025)

(EDS). The sessions is considered completed and a transfer to the next sessions happens when performance reach 80% (moving average, window=20 trials). Sessions initially consisted of 60 trials and were extended in blocks of 60 trials until completed.

Each session used a distinct set of stimuli. For each session, one modality was designated as task-relevant and contained the GO and NOGO stimuli, while stimuli from the other modality were task-irrelevant and had no influence on performance or feedback.

The relevant modality in the first intra-dimensional shift (IDS) session was the same as during training. This modality remained constant throughout the subsequent staircase and attention manipulation sessions. A modality shift occurred at the extra-dimensional shift (EDS) session, where the relevant modality changed. Following the first EDS session, a new cycle began with an IDS in the same modality as the preceding EDS. The same structure was then repeated, with the relevant modality shifting back to the original modality at the second EDS session.

The difficulty of the AMS sessions was manipulated by requiring participants to perform the task either with the same stimulus set used in the preceding IDS session (easy discrimination) or with the NOGO stimulus adjusted during the staircase session to be perceptually closer to the GO stimulus (difficult discrimination). Each AMS session consisted of two blocks (120 trials total), and each participant completed one easy and one difficult AMS session, occurring in either the first or the second cycle.

Reaction Time Estimation

Reaction time (RT) was defined as the interval between stimulus onset and the participant's key press. RT analyses included only trials in which a response occurred within the 1-s stimulus presentation window. Session mean RTs were computed using a trimmed mean, excluding the highest and lowest 10% of RT values.

For the purpose of our study, RT shift cost is defined as the within-participant change in average response speed from the intra-dimensional learning session (IDS) to the following extra-dimensional learning session (EDS). This measure allows direct comparison with the learning shift cost dynamics.

Performance Control

The attention manipulation depended on achieving appropriate task difficulty following the staircase procedure. To quantify performance impact, we computed a combined measure incorporating both accuracy and reaction time. Specifically, performance was expressed as the Euclidean distance between normalised error rate and normalised reaction time for sessions following the attention manipulation (Figure 1D). A minimum acceptable performance impact threshold was defined based on a control subset of participants for whom task difficulty was explicitly regulated: if post-staircase accuracy fell below 55% (indicating guessing) or exceeded 75% (indicating insufficient difficulty), the staircase procedure was repeated to ensure interpretable performance. Participants who did not meet the minimum Euclidean distance criterion were excluded from further analyses.

Learning Point and Shift Cost Estimation

Learning-related measures were estimated to characterise task progression and to facilitate comparison with prior analyses of this experiment. Learning point was defined as the trial at which performance reliably exceeded chance. Learning points were estimated using a Bayesian evidence-updating framework distinguishing acquisition and consolidation stages. The learning point was operationalised as the trial at which the 3% highest density interval of the posterior probability of a correct response exceeded 0.5. Shift costs were calculated as the difference between the learning points of the EDS session and the preceding IDS session, indexing the additional trials required to complete learning following the shift. See Postnova et al. (2025) for learning point estimation details.

Results

Mean Reaction Times Across Sessions

We first examined how reaction times (RTs) changed across sessions, focusing on the effects of task progression and modality order.

Mean RTs were computed for each session, separately for participants trained initially in the visual (VIS-first) or auditory (AUD-first) modality. Figure 2 shows the session-by-session progression of RTs for each training group. For participants in the VIS-first group, RTs increased noticeably when transitioning from visual to auditory during the first extra-dimensional shift (EDS). When shifting back from auditory to visual in the second EDS, RTs decreased toward their initial levels but did not fully return, consistent with residual inhibition of the previously dominant modality. In contrast, participants in the AUD-first group exhibited relatively stable RTs across all sessions, with no clear changes following modality shifts. Although a Friedman test comparing RTs in the VIS-first group did not reach statistical significance ($\chi^2(2) = 5.556$, $p = 0.062$), *post-hoc* Wilcoxon signed-rank tests suggested a trend toward slower RTs from IDS1 to EDS1 ($p_{\text{corrected}} = 0.082$), consistent with the descriptive pattern observed in Figure 2.

Analyses comparing shifts following difficult versus easy tasks revealed no clear effect of prior task difficulty on RTs, or, if present, this effect was much smaller than the influence of modality progression itself.

RT shift cost

To further quantify the impact of modality shifts on reaction time, we computed RT shift cost as the difference between each extra-dimensional shift (EDS) and the preceding intra-dimensional shift (IDS). This measure was chosen to align with our learning-time shift-cost approach and to assess difficulty-related carryover effects on RT following the shift.

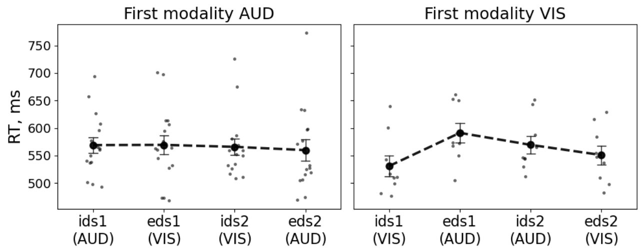


Figure 2: Mean reaction times (± SEM) are shown separately for participants trained first in the auditory (left) and visual (right) modality. Dotted lines connect sessions to highlight changes in reaction time across stages.

Figure 3A shows RT shift cost for participants performing VIS→AUD and AUD→VIS shifts. The pattern of results reflects the influence of modality dominance: participants trained initially in the visual modality exhibited the largest RT shift cost when moving from VIS to AUD, indicating that this transition was particularly demanding. In contrast, for participants trained in the auditory modality, the shift from AUD to VIS was associated with a negligible RT shift cost.

Figure 3B displays RT shift cost for sessions preceded by easy versus difficult attention-manipulation tasks. No systematic differences were observed between difficulty conditions, indicating that task difficulty had little influence on RTs, in contrast to the pronounced effect of modality progression during the first shift.

Linear regression analysis did not provide evidence that prior task difficulty did not affect RT shift cost, whereas both cycle order — higher change in the first cycle — and modality shift direction — VIS→AUD larger than AUD→VIS — had significant effects (R^2 = 0.176, *F(4, 45)*=2.40, *p[cycle]*=0.21, *p[modality shift]*=0.047).

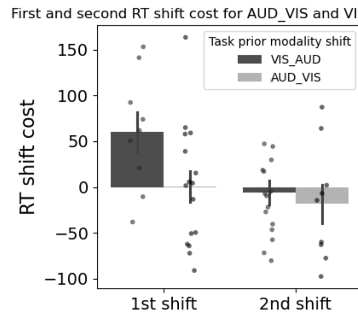
Overall, these results highlight that the direction of the modality shift and dominance of the initially trained modality strongly shape RT shift cost, whereas task difficulty has no or little influence on these patterns.

Relationship Between Pre-Shift RT and Learning Shift Cost

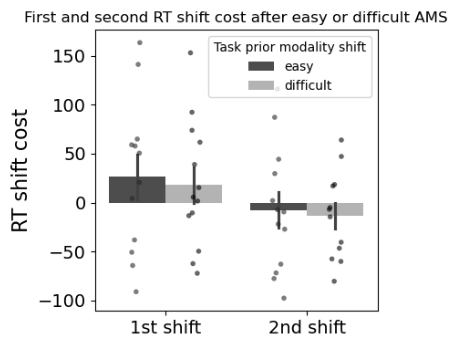
Building on prior research suggesting that processing time prior to a shift can influence shift costs (Roebuck et al., 2019), we examined whether reaction times in the session immediately preceding a modality shift (the AMS session) were related to subsequent learning shift costs, measured as the difference in number of trials required to reach the learning point before and after the shift.

The results indicated that higher RTs in the preceding AMS session strongly correlated with larger subsequent learning shift costs, and that the first cycle was associated with significantly larger shift costs than the second (see Figure 3C; linear regression model R^2 = 0.321, *F(2, 47)*=11.12, *p[cycle]*=0.14, *p[previous stage RT]*<0.001). These patterns are consistent with previously reported effects of task difficulty on shift costs, as more challenging discrimination tasks produced longer RTs and correspondingly larger subsequent learning costs.

A.



B.



C.

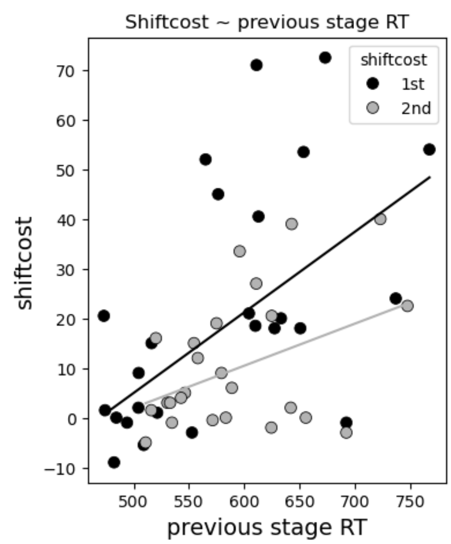


Figure 3: **Panel A**: RT shift cost are shown separately for the first and second cycles, and for shifts from visual to auditory (VIS→AUD) and auditory to visual (AUD→VIS). Error bars indicate standard error of the mean. **Panel B**: RT shift cost are shown separately for the first and second cycles, and for shifts following easy or difficult discrimination task. Error bars indicate standard error of the mean. **Panel C**: Shift cost as a function of preceding-session RT. Black and grey lines show the first and second cycles, respectively, illustrating the positive relationship between prior RT and subsequent shift cost.

Overall, while learning times are prolonged after modality shifts – especially following difficult attention manipulations – reaction times follow a distinct pattern. RTs are primarily influenced by the initially trained modality: VIS-first participants exhibit slower responses when shifting to auditory, consistent with a dominant visual processing effect, whereas AUD-first participants show little RT modulation across shifts. These results indicate that modality dominance, rather than task difficulty, drives the observed RT patterns, highlighting a dissociation between learning-time costs and processing-speed costs.

Discussion

The present study examined whether reaction time captures the same attentional shift costs observed in learning-based measures within an attentional set-shifting paradigm. Speed–accuracy trade-offs are often studied as joint considerations of response speed and accuracy. In the present study, we observed that RT and accuracy-based learning measures reflect different aspects of performance during acquisition and are therefore analysed separately. While earlier analyses using this task demonstrated that learning following a modality shift is further prolonged when the shift is preceded by a perceptually demanding discrimination (Postnova et al., 2025), the current results reveal a different pattern for RTs. Together, these findings suggest that learning-based and RT-based indices of shift cost reflect partially dissociable attentional mechanisms and source of the cost (Kiesel et al., 2010; Monsell, 2003; Wylie & Allport, 2000).

RT dynamics were primarily shaped by the modality in which participants were initially trained, rather than by the perceptual difficulty of the task preceding the shift. Participants who trained first in the visual modality showed a pronounced increase in RT when shifting from visual to auditory processing, whereas the reverse shift – for participants who trained first in auditory modality – incurred little to no RT cost. This asymmetry was most evident during the first modality transition and was attenuated during the second cycle, after participants had acquired experience in both modalities. This pattern is consistent with the notion of modality dominance, whereby task control settings established in an initially trained dominant modality persist, and interfere with subsequent processing in a non-dominant modality (McGovern et al., 2016; Sandhu, 2021; Sandhu & Dyson, 2013; Wylie & Allport, 2000).

Notably, task difficulty showed no modulation of RT-based shift costs. Shifts following the difficult discrimination did not produce larger RT shift costs than those following the easier discrimination, indicating that perceptual demand does not directly influence RT adjustment across modality changes, or its effect on RT shift cost is negligible compared to the modality dominance effect. This contrasts with learning-based shift costs in the same task, which were reliably amplified following the difficult discrimination task. The absence of a detectable difficulty effect on RT suggests that immediate processing speed and learning dynamics are governed by distinct control processes, consistent with the view that different sources of cost contribute distinctly to various behavioural measures (Quinlan & Hill, 1999; Spence et al., 2001).

Nevertheless, RT and learning-based measures were not independent. Mean RT during the session preceding the shift predicted the magnitude of the subsequent learning shift cost, with higher (pre-shift) RTs associated with greater (post-shift) learning delays. This relationship indicates that while perceptual difficulty and processing time do not directly shape RT shift costs, they nonetheless influence higher-level mechanisms involved in acquiring new stimulus–response contingencies. In this sense, processing demands appear to affect learning indirectly, through their cumulative impact on attentional and cognitive resources, rather than through immediate changes in response speed.

These findings refine recent accounts proposing that processing time, rather than modality, determines shift costs (Roebuck et al., 2019). In the present task, changes in mean processing time were instead dominated by modality-specific control dynamics, but remained functionally linked to learning outcomes, supporting a view in which attentional set shifting engages multiple mechanisms operating at different temporal scales: rapid, modality-dependent control adjustments reflected in RT, and slower, resource-sensitive learning processes reflected in trials-to-criterion.

Taken together, the results indicate that *shift costs* are not a single phenomenon: session-level shift costs measured in mean RT, accuracy, and learning time each capture distinct mechanisms and reflect partially-separable cognitive processes. RT-based measures primarily index residual inhibition or persistence of modality-specific control settings, whereas learning-based measures capture the effects of attentional demand on the acquisition and consolidation of new contingencies. Recognising this dissociation helps reconcile mixed findings in the set-shifting literature, and underscores the importance of considering which component of attentional control is indexed by a given behavioural measure.

Limitations and Future studies

A key limitation of the present study is that RT was analysed at the session level rather than on a trial-by-trial basis, which is more typical in studies of modality shift costs and sensory switching (Kiesel et al., 2010). This choice reflects the structure of the task, in which performance dynamically evolved within each session as participants learned new contingencies, making trial-level RT difficult to interpret independently of learning stage. Moreover, both the attentional manipulation and the modality shifts were implemented at the session level, motivating a session-averaged approach that is directly comparable to learning-based shift costs. Despite this higher-level analysis, robust modality-related asymmetries in RT were still observed, suggesting that such effects can emerge beyond trial-level dynamics. A related methodological constraint is that RT shift effects were computed relative to the chronologically preceding session rather than to a baseline within the same modality, as is common in psychophysical studies (Kiesel et al., 2010). While this preserves the temporal structure of the experiment and enables comparison with learning shift costs, future studies could explicitly incorporate within-modality baselines or redesign the task to align baseline RT and learning measures more closely. Additionally, extending the paradigm to include a third sensory modality may help disentangle modality dominance from inhibitory mechanisms and further clarify the processes underlying different expressions of shift cost (Spence et al., 2001).

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