When learning hurts control: inducing cross-task-covariance causes multitasking costs

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Analysis code: <https://github.com/kel-github/statistual-mt-analysis>

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Abstract

Performing two tasks concurrently typically leads to performance costs. Historically, multitasking costs have been assumed to reflect fundamental constraints of cognitive architectures. A new perspective proposes that multitasking costs reflect information sharing between constituent tasks; shared information gains representational efficiency, at the expense of multitasking capability. We test this theory by determining whether increasing cross-task information harms multitasking. 48 participants performed multitasks where they mapped keypresses to four shapes. In a subsequent statistical learning task, these shapes then formed pairs that were predictive or non-predictive of an upcoming target judgement. When participants again responded to these shapes in the multitasking context, performance was poorer when the shape pair had been predictive of target outcomes in the learning phase, relative to non-predictive. Thus, associating common information to shape pairings transferred to negatively impact multitasking performance, providing the first causal evidence for the shared representational account of multitasking performance.

Introduction

Arguably the most pervasive and studied aspect of human brain function is its information-processing capacity. Despite its sophisticated circuitry, the brain shows performance impairments across multiple domains, including perception, memory and decision-making, when analysing multiple sources of information concurrently. This is the case even in situations where the stimuli and responses are relatively simple and their load on the system appears minimal (Marois & Ivanoff, 2005; Pashler, 1994).

These seemingly ubiquitous limitations of human information processing are perhaps surprising given the brain's remarkable ability to rapidly learn and adapt behavioural repertoires, to generalise across stimuli and tasks (Hilgard & Bower, 1966; Weaver, 2015), and importantly, to modify capacity via learning. Indeed, a key finding from classic multitasking paradigms like the psychological refractory period (PRP) is that the associated dual-tasks costs are reduced following practice (see Garner & Dux, in press; Strobach & Torsten, 2017 for reviews). Interestingly, practice benefits gained from performing the constituent tasks tend to show minimal, if any, transfer to similar tasks (Garner et al., 2014; Strobach & Torsten, 2017). Thus, collectively, these findings imply a trade off between efficient multitasking performance and generalisability, provoking the puzzle; are multitasking costs a consequence of flexible and generalisable performance?

Instead of considering what gains multitasking limitations may reflect, the dominant accounts over the last three decades have explained multitasking performance decrements in terms of *how* they occur, by characterising the conditions that impact performance and often linking these to brain activity. For example, the central bottleneck account (e.g. Pashler, 1994) predicts that multitasking costs result from response-selection operations only being able to be conducted serially, thus a second task must wait for the first to be completed giving rise to response slowing/multitasking costs. Shared resource models propose instead that response selection can occur in parallel for multiple tasks, but these resources are differentially weighted across the tasks, leading to reaction time slowing for some tasks relative to others (Navon & Miller, 2002; Tombu & Jolicoeur, 2003). Finally, control theories hypothesise that multitasking costs do not reflect resource limitations per se but rather a procedural cost implemented by the executive control system in order to optimize performance in dual-task conditions and avoid interference (Logan & Gordon, 2001; Meyer & Kieras, 1997; see also Salvucci & Taatgen, 2008).

We have proposed an alternate source of multitasking performance limitations; namely the extent to which internal representations share overlap between tasks in the networks that underpin performance (Garner & Dux, 2015). In support of this idea, we have shown using machine learning analyses of fMRI data that practice related reductions in multitasking costs are associated with the extent to which task-related information becomes distinct from that of other tasks in a prefrontal-parietal-striatal network. Moreover, in support of the link between multitasking and performance generalisability, Musslick & Cohen (2021) have shown that neural networks that allow overlap between task representations show both

decrements in multitasking performance and more rapid acquisition of new tasks. Importantly, representational sharing rapidly attenuates multitasking performance independent of network size (Petri et al., 2021), perhaps accounting for how a system as complex as the human brain can still show striking multitasking limitations.

Currently, it remains to be determined what conditions induce representation sharing between tasks. To integrate the above findings, we recently proposed that task representations overlap to the extent that information can be leveraged to predict common outcomes (Garner & Dux, in press). Collectively, this new framework for characterising cognitive control limitations, focussing instead on *why* multitasking costs occur in such an adaptive system like the brain, gives rise to the key hypothesis that increasing the extent to which stimuli predict common outcomes should be harmful for multitasking costs.

Here we address this hypothesis in a pre-registered experiment. Subjects completed a multitasking paradigm where they mapped key press responses to four shapes. In order to induce shared information between tasks, in a subsequent statistical learning task these four shapes were combined into pairs that were predictive or non-predictive of the identity of an upcoming visual orientation target - a task that was unrelated to the multitasking paradigm. Significant learning was observed, thus post-learning the predictive stimuli were associated in terms of jointly predicting a common outcome, which we assume induces overlap in the brain's internal representation of those stimuli. Indeed, there exists evidence that this occurs in the circuits underlying object representation. Schapiro, Kustner and Turk-browne (2012) used high resolution fMRI and multivoxel pattern analysis to demonstrate that neural responses to objects in cortical and hippocampal areas of human medial temporal lobe become more similar across time as those objects become more associated. Following learning, participants responded to these shapes once again in the multitasking context. To preview the results, performance gains were poorer when the shape pair had previously been predictive of task outcomes in the statistical learning phase, relative to being non-predictive. Thus, learning associations between stimuli transferred to the multitasking context, and negatively impacted performance.

Method

All aspects of the project were pre-registered at the Open Science Framework (see <https://osf.io/em8xd>) except where specified.

Participants

Participants were drawn from the credit and paid participation pools run by the School of Psychology at The University of Queensland. Our stopping rule had a two-pronged approach: We planned to stop if we observed, using a paired Bayesian t-test, substantial evidence (employing Jeffreys (1961) classification for the strength of evidence) for or against the alternate hypothesis that our statistical learning manipulation induced changes to MT costs, or that we reached the total number of subjects for a complete counterbalancing of shape to response-mappings (48 subjects). We opted for this upper limit for pragmatic reasons as this was part of a year long 4th year honour project. We had a final sample size of 48. Participants were required to have normal or corrected-to-normal visual acuity, and to not have a

psychiatric or neurological diagnosis (18 of the final 48 participants chose to confirm that they did not have such a diagnosis, the remaining participants declined to respond). A total of 62 participants took part. Of these, 13 participants were removed for not achieving >85% accuracy in the first multitasking paradigm while one was removed due to technical error. The 48 participants retained were between the ages of 17 and 35 years (mean age: approximately 22 years) and included 37 of the female sex and 11 of the male sex (42 right-handed) .

Materials

Tasks were programmed in MATLAB using the Psychophysics Toolbox 3 extension and presented via Mac Minis (2014, 2.6 GHz Intel Core i5) on a 24 inch ASUS NVIDIA 9 (VG248) monitor. Bayesian analyses were conducted using the BayesFactor (Morey et al., 2015) package in R v4.0.3 (R Core Team, 2015), using R Studio (v1.1.456, RStudio Team, 2020) and implementing the relevant default priors (Rouder et al., 2009, 2012). All data, task and analysis code are available online¹. Throughout the experiment, participants were presented with 4 black visual shapes (now called A, B, C & D) taken from Fiser & Aslin (2001) that appeared on a white background, subtending approximately 1° of visual angle at a viewing distance of 57cm (Figure 1). Participants responded using a standard Mac keyboard using the “D” (for shape A), “F” (B), “J” (C) and “K” (D) keys, using the first two fingers of each hand. Participants were instructed to respond as accurately and efficiently as possible.

Experimental Design

Participants completed four phases over 2-2.5 hours and the manipulations were conducted completely within-subjects. The phases included: Response Mapping, Multitasking (MT) pre, Statistical Learning (SL) and MT post. During response mapping participants learnt which key to press in response to each shape for the MT paradigm. During the first MT phase we assessed baseline multitasking performance, before participants completed the SL phase. SL was employed in order to manipulate the extent to which stimuli shared information, with a view to investigating our key hypothesis that increased covariance between tasks leads to larger multitasking costs which was assessed in the 4th phase: MT post.

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Figure 1: Task and experimental phases. A) Multitasking phases were performed pre and post the statistical learning phase (see B). One (single task, ST) or two (multitask, MT) shapes appeared above or below fixation. Participants were required to respond as efficiently as possible via key press to the stimulus/stimuli. B) The stimuli for the statistical learning (SL) task were similar to the MT trials, but shapes only appeared as pairs prior to a target stimulus to which the participant made an orientation judgement. Participants were required to perform a 2 alternative discrimination on the target orientation as accurately and efficiently as possible. Shape pairings were formed to be predictive ($p=.8/.2$) or non-predictive ($p=.5$) of target identity. C) Theoretical depiction of the stimulus response mappings post SL learning, for the MT task (second phase). Thick line denotes task-relevant associations between stimulus and response for the MT phase, thin lines those established during the SL task. Note (for example) that as the shapes 'a' and 'c' jointly predicted the likely relevance of the 'F' key in the SL paradigm, they are now expected to cause greater interference to performance in the MT context, relative to 'a' and 'd', which were jointly non-predictive of outcomes in the SL paradigm.

Response Mapping Phase. Here participants learned which shapes went with which keypresses for the MT phases. On each trial, a fixation cross surrounded by a rectangular grey border (1.2° w x 3.2° h) was presented in the centre of the screen for between 700-800 ms (determined randomly). Following this, one of the four shapes appeared in the rectangle, spanning 1° with its centre placed 1.5° above or below the fixation cross for 750 ms. Subsequently, the fixation cross was presented until response. Participants were instructed to press the key that corresponded to the shape as efficiently as possible via key press ('d', 'f', 'j', or 'k'), using the first two fingers of each hand. These trials shall be referred to hereon as single-task trials (ST). Following the response, accuracy feedback (Correct :')/Incorrect :(') was presented for 750 ms. The fixation cross was presented for an inter-trial interval of 1500 ms. The task ended when the participant scored a minimum of 90% correct on the 20 most recently performed trials. The shape-keypress mappings were fully counterbalanced across participants.

Multitasking Phases. The display and trial procedures were the same as the response mapping phase with the following exceptions; multitask (MT) trials were presented in addition to ST trials and no performance feedback was presented. On MT trials, two shapes were simultaneously presented (above and below fixation, see Figure 1A) with the inner edges separated by a distance of 0.5° . Participants were instructed to respond to all the shapes they saw (1 or 2) as efficiently as possible via the appropriate keypresses. Trial types (ST, MT) appeared equally often; each shape (a, b, c or d) and shape pair (ac, ad, bc, or bd) was presented 50 times across the phase, for a total of 400 trials. Trial order was pseudo randomised for each participant. Participants were instructed to take a break at the end of each 20 trials. Between the pre and post MT phases the SL was presented.

Statistical Learning Phase. The SL trials began similarly to the MT trials described above, however, 2 shapes were always presented and were always followed by a target stimulus to which participants responded instead (see Figure 1B). Specifically, 500 ms after shape pair offset, the fixation cross was replaced by a circle with a line through its centre for 67 ms, oriented at either 45° (clockwise) or 315° (counterclockwise) and subtending 1° . Participants were instructed to identify whether the target was oriented clockwise or counterclockwise and to press the 'f' key or the 'j' key accordingly (target orientation to keypress was counterbalanced across participants). In order to manipulate the extent to which the shape pairs predicted common outcomes, shape pairings were assigned as predictive ($p=.8/.2$) or non-predictive ($p=.5$) of target identity. Importantly, predictive pairings comprised 'ac', and 'bd', whereas 'ad' and 'bc' formed non-predictive pairings (see Figure 1B). Whether pairs 'ac' and 'bd' were predictive of clockwise or counterclockwise targets was fully counterbalanced over participants. Thus, 'ac' and 'bd' pairs became associated with common outcomes, whereas 'ad' and 'bc' did not. Trial types were fully counterbalanced over each set of 80 trials, of which participants completed 7 blocks.

Results

All analyses were planned and pre-registered at the Open Science Framework (see <https://osf.io/em8xd>) and exceptions are noted.

Data Cleaning

Trials were included if their associated reaction times were greater than 250 ms and less than 2.5 standard deviations above the mean RT for each subject and condition. Using this approach, outliers comprised less than 3% of trials.

Multitasking-Pre

Our paradigm elicited a typical multitasking cost with slower reaction times for multitask trials ($M = 1110$ ms, $SD: 171$) compared to single task trials ($M = 718$ ms, $SD = 131$) in the pre-session (see Figure 2). This was confirmed with a Bayesian paired sample t-test showing large evidence $BF_{10} = 1.05e+30$ (error % = 0) in support of the alternate hypothesis that RTs differ between conditions (MT vs. ST). Accuracy was $>.89$ across subjects.

Figure 2: Performance over the two MT phases. A) M RTs ([s], y-axis) for ST trials were faster relative to MT trials with both predictive (p) and non-predictive (np) shape

pairings (x-axis). Note that at this stage, p and np relationships were yet to be established. B) MT costs were computed by taking the ratio of RTs (s) on MT trials relative to ST trials, for np and p shapes at both the pre (pr) and post (po) MT session. C) Densities of δ MT costs from pre- to post- for np and p shapes (s). δ MT was larger for np shapes than for p shapes. Error bars reflect the standard error of the mean (SEM).

Statistical Learning

Some evidence for learning was observed with the predictiveness of the shape pairing influencing RT for the orientation judgement (Figure 3). Specifically, a Bayesian 3 ($p(\text{target}|\text{cue})=.8, .5, .2$) $\times$ 8 (block) analysis of variance (ANOVA)² showed non-conclusive evidence for the models that contained a main effect of block ($BF_{10} = 1.99$, error % 0.4), or probability ($BF_{10} = 0.57$, error % 1.93) or both ($BF_{10} = 1.21$, error % = 0.81), and evidence against the model that contained a block $\times$ probability interaction ($BF_{10} = .001$, error % 0.85). As this evidence was not conclusive but given we find the anticipated impact of SL pairings on MT performance (see below), we interrogated the data further using an exploratory post-hoc Null Hypothesis Significance Testing approach. The 3 $\times$ 8 ANOVA showed significant main effects for both predictiveness ($F(1.07, 48.06) = 4.75$, $p = .011$, $\eta_p^2 = .09$) and block ($F(2.73, 122.73) = 2.13$, $p = .04$, $\eta_p^2 = .05$). Numerically, RTs were slowest for the $p=.2$ condition ($M = 509$ ms, $SD = 200$) relative to the $p = .5$ ($M = 488$ ms, $SD = 115$) and the $p = .8$ ($M = 494$ ms, $SD = 129$) conditions. Again accuracy here was high, with subjects scoring an average of $p = .95$.

² Note in the pre-registration we had specified we would perform a one way ANOVA with 3 levels (for $p(\text{target}|\text{cues})$), however this had erroneously neglected to include the block factor (1:8), which we have corrected here.

Figure 3: *M* RT (s) performance in the SL paradigm for each outcome probability ($p=.2$ | $.5$ | $.8$) across the 8 blocks. Error bars reflect SEM.

Multitasking-Post

The key result of the present study concerned the extent to which the learning manipulation influenced multitasking performance. To wit, do shape pairings that were predictive of the target orientation in the SL phase lead to larger costs when presented in the multitasking paradigm? In order to assess this, multitasking costs were quantified by taking the ratio of RTs on MT to ST trials (MT/ST), yielding one MT score for each stimulus shape and condition. The MT scores were then averaged across shapes, according to whether the shape had appeared in the pairing that made it predictive or non-predictive of target outcomes in the SL task. Difference scores were then computed between pre and post sessions, yielding a change MT cost score for predictive vs. non-predictive shape pairs. Note that a more positive change score reflects a greater improvement in performance. The specific prediction is that change scores should be larger for non-predictive shape pairings than for predictive shape pairings, as the statistical associations from the SL stage should

impinge any performance improvements under MT conditions. Moderate evidence was observed in support for this alternate hypothesis $BF_{10} = 7.82$ (error % 0), as MT change scores were low for predictive stimuli ($M = -0.04$ ms, $SD = 132$), relative to non-predictive stimuli ($M = 47$ ms, $SD = 131$, see Figure 1C). Thus, we find evidence that multitasking performance gains were selectively impaired when stimuli conjointly predicted outcomes irrelevant to the current task. Accuracy across the conditions at the post-MT stage was high, with a minimum of $p = .83$ across participants.

Discussion

Here we sought to test a key prediction of a recently introduced theory of multitasking and learning (Garner & Dux, in press; Musslick & Cohen, 2021). Specifically, this theory predicts that the brain leverages shared variance between tasks for representational efficiency, and that this occurs at the direct expense of multitasking ability, given that the two task-representations are now more co-dependent. Thus tasks that share information, i.e. that are predictive of common outcomes, should cause greater interference to performance when combined in a multitasking context, even when those outcomes are not relevant to the current task. Here we observed support for this prediction. Stimuli that made conjoint predictions regarding a speeded orientation judgment in an unrelated statistical learning paradigm lead to larger costs when they appeared in a multitasking context.

Although there was substantial evidence that exposure to predictive pairings in the SL task impacted MT performance as expected, the evidence for the learning effect in the SL data itself was relatively weak. Thus it is appropriate to ask if there are alternative explanations for the pattern of results observed in the MT data? Crucially, in the statistical learning phase all stimuli appeared an equal number of times across the predictive and non-predictive conditions and the shape mappings were counterbalanced across participants. Thus, learning the predictiveness of the stimuli for particular outcomes appears to be the most parsimonious account for the current MT results. Indeed, the impact of the SL phase on the MT data implies that the learning effect was robust enough to transfer from a single learning session to impact performance on an unrelated MT paradigm. Of note, the same key press responses were used in both the SL and MT phases, consequently one cannot determine the level of processing at which the observed effect occurred, as it could have an influence right up to response execution/motor operations. In future work we seek to better model the SL data, to understand how best to assess the presence or absence of learning effects and the level of information processing at which they occur. Nevertheless, the present results clearly illustrate that stimuli which share information about outcomes are more difficult to process during multitasking.

The present results and the theory they are based on also shed new light on other findings from the multitasking literature. Schacherer and Hazeltine (2021) recently found in a dual-task study with visual and auditory stimulus and response modalities that dual-task costs were larger when the relationship between the stimuli and action effects (e.g., a sound played after a key press response to a visual stimulus) had high conceptual overlap between tasks rather than within tasks (e.g., picture of a pig for one stimulus and an oink sound for a different stimulus vs. a picture of a pig and an oink sound for the same stimulus). Similarly, Li and Li (2021) observed in a

combined dual-task visual working memory and multiple-object tracking study that recall precision in the memory task was only impaired when the tasks shared overlapping modalities (i.e., both tapping spatial judgements as opposed to tapping spatial and identity judgments). Collectively both these results fit nicely within our framework, where it is shared representational variance between tasks that drives multitasking costs. Here we present the first causal evidence for the representational mechanism that may drive sharing and multitasking costs, that being the relationship of events to future outcomes.

A final contribution of the present work is that it offers, we believe, the first example where brain imaging findings have motivated multitasking theory (e.g. Coltheart, 2006) which makes a direct testable prediction for dual-tasking behaviour. The present work shows how imaging results and behavioural approaches can be married together to tell us important things about cognition (Garner & Dux, in press; Musslick & Cohen, 2021); in this case the role played by overlapping representations between tasks in driving multitasking costs.

Open Practices Statement

The study was pre-registered on the Open Science Framework (<https://osf.io/em8xd>). The data are openly available on the UQ eSpace repository (<https://doi.org/10.48610/dc3a817>). Custom code for task presentation (<https://github.com/kel-github/statistual-multitasking-task-code>) and data analysis (<https://github.com/kel-github/statistual-mt-analysis>) are both available on Github.

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