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Title: Investigating the Role of Executive Resources across Aesthetic and Non-Aesthetic Judgments

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Abstract

Aesthetic judgments dominate much of daily life by guiding how we evaluate objects, people, and experiences in our environment. One key question that remains unanswered is the extent to which more specialised or largely general cognitive resources support aesthetic judgments. To investigate this question in the context of executive resources, we examined the extent to which a central working memory load produces similar or different reaction time interference on aesthetic compared to non-aesthetic judgments. Across three pre-registered experiments that used Bayesian multi-level modelling approaches (N>100 per experiment), we found clear evidence that a central working memory load produces similar reaction time interference on aesthetic judgments relative to non-aesthetic (motion) judgments. We also showed that this similarity in processing across aesthetic versus non-aesthetic judgments holds across variations in the form of art (people vs landscape; Exps. 1-3), medium type (artwork vs photographs; Exp. 2) and load content (art images vs letters; Exps. 1-3). These findings suggest that across a range of experimental contexts, as well as different processing streams in working memory (e.g., visual vs verbal), aesthetic and motion judgments commonly rely on a domain-general executive system, rather than a system that is more specifically tied to aesthetic judgments. In doing so, these findings shine new light on the cognitive architecture that supports aesthetic judgments, as well as how domain-general executive systems operate more generally in cognition.

1. General Introduction

Fascination with art is a universal and timeless human phenomenon (Dutton, 2009; Lamarque, 1999). From creating art to visiting galleries and attending live performances, people are frequently captivated by the aesthetic appeal of art. Likewise, interest in studying art across the scientific community has led to a programme of research that investigates aesthetic experiences from psychological and neuroscientific perspectives (Augustin et al., 2012; Berlyne, 1971; Cattaneo, 2019; Chatterjee, 2003; Fechner, 1876; Iigaya et al., 2020; Jacobsen, 2006; Kirsch et al., 2016; Nadal & Chatterjee, 2019; Nadal & Skov, 2015; Palmer et al., 2013; Pearce et al., 2016; Van de Cruys & Wagemans, 2011; Zeki, 1999). Yet understanding of the cognitive architecture that supports aesthetic judgments remains in its infancy. Given the vital role of aesthetics in guiding how we appraise objects, people, and experiences in our environment, the current work investigates the type of executive control mechanisms that support aesthetic judgments.

The cognitive processes that underpin aesthetic judgments have often been characterised using dual-processing frameworks, which distinguish automatic from more controlled processing stages (Chatterjee, 2003; Chatterjee & Vartanian, 2014; Graf & Landwehr, 2015; Leder et al., 2004; Leder & Nadal, 2014; Locher et al., 2007; Locher et al., 2010; Pearce et al., 2016; Pelowski & Akiba, 2011; Redies, 2015) For example, Leder and colleagues (2004) proposed that aesthetic judgments represent the end-product of a sequential cascade of five information processing stages that include automatic and controlled processes and span sensory-perceptual signals, cognitive mastering, and deliberate evaluation stages. Although it seems likely, or even necessary, that a form of executive control would be required during aesthetic judgments, the type and structure of such executive control remains largely unknown. Moreover, the extent to which aesthetic judgments rely upon general executive control mechanisms, which operate across many domains, or more specific mechanisms, that are partially tied to aesthetic contexts, remains unclear.

One way to probe the operation of executive functions is to use dual-task paradigms, whereby a demanding secondary task is performed alongside a main task of interest (Lavie et al., 2004; Satpute & Lieberman, 2006). A typical dual-task approach would require participants to hold in memory one letter (low load) or six letters (high load) while quickly and accurately performing the primary task. According to load theory (Lavie et al., 2005; 2010), executive functions, such as working memory, help to maintain response priorities throughout a task. Consequently, when executive control functions are loaded with a demanding secondary task, the control capacity that maintains task priority is reduced, leading to increased distractor interference that perturbs the main task response. In cases when higher load interferes with the main task, it has been suggested that mental operations required during the main task are relatively resource-intensive and reliant on controlled and effortful processes. In contrast, in cases when higher load does not interference with the main task, it suggests that mental operations required during the main task are resource-light, relatively efficient, and less reliant on controlled or effortful processes. As such, dual-task paradigms are a useful way to characterise the type of executive resources that are relied upon in a given context.

A small number of previous studies have investigated the type of cognitive systems that underpin aesthetics judgments using dual-task paradigms. Brielmann and Pelli (2017) found that adding a secondary two-back task decreased aesthetic judgments for beautiful stimuli, but not for non-beautiful stimuli. Likewise, Che and colleagues (2021) showed that a demanding secondary task delayed judgments of beauty, but not liking. These findings suggest that, during aesthetic judgments, different stimulus and task features place more demands on effortful operations of the central executive. Conversely, Mullennix and colleagues (2013) showed that aesthetic ratings were not affected by a secondary load task. This latter finding suggests that, at least in some instances, aesthetic judgments remain unaffected by higher load and can be processed in a relatively automatic manner.

These prior studies of aesthetics using secondary tasks have all used art-based stimuli and aesthetically-oriented tasks, such as judgments of beauty and liking. Such experimental designs are useful for probing information processing structures within aesthetic contexts. However, these designs are unable to address the extent to which common or distinct forms of executive control are deployed across aesthetic compared to non-aesthetic judgments. As such, open questions remain concerning domain-specificity in aesthetic judgments, and contrasting theoretical possibilities exist. A domain-specific account would suggest that aesthetic judgments draw upon distinct sets of cognitive control processes (Goldman, 2001; Guyer, 2005). One prediction that follows from this account is that aesthetic judgments may rely on partially distinct executive resources compared to non-aesthetic judgments. In contrast, a domain-general account would suggest that the same set of executive resources will be deployed in a similar manner across aesthetic and non-aesthetic contexts. For example, a semantic cognition account of aesthetics predicts that similar cognitive and brain systems that are engaged in extracting meaning from the environment in general (i.e., non-aesthetic contexts), such as modality-specific conceptual representations and controlled executive processes, would be similarly involved in aesthetic judgments (Bara et al., 2021).

Therefore, the overarching aim of the current study is to investigate the extent to which domain-general or domain-specific executive control mechanisms are deployed during aesthetic compared to non-aesthetic judgments. More specifically, the question we address here is the extent to which central working memory load produces similar or different reaction time interference on aesthetic judgments compared to non-aesthetic judgments. By using a Bayesian analytical framework (rather than null-hypothesis significance testing), we can provide supporting evidence for the domain-general or domain-specific accounts. In other words, we can provide support for a similarity in interference, as well as a difference in interference, between aesthetic and non-aesthetic contexts. Across three pre-registered experiments, we test these hypotheses by varying the type of judgment, the type of stimuli, and the type of load content between aesthetic and non-aesthetic categories. By doing so, we are able to test the extent to which the pattern of results generalises across different stimulus features and task contexts.

2. Experiment 1

2.1 Introduction

In Experiment 1, we investigated to what extent high cognitive load produces greater reaction time interference on aesthetic judgments relative to non-aesthetic judgments. To do so, we compared aesthetic with implied motion judgments towards the same art stimuli. Greater interference in aesthetic than non-aesthetic judgments would support the view that somewhat specialised executive resources are deployed during aesthetic judgments. In contrast, equivalent interference between aesthetic and non-aesthetic judgments would support the view that a largely general cognitive architecture supports aesthetic judgments.

2.2 Method

2.2.1 Pre-registration and Open Science statement

Across all three experiments, the research questions, hypotheses, planned analyses, sample sizes and exclusion criteria were pre-registered. For Experiment 1, the pre-registration can be found at https://aspredicted.org/blind.php?x=4uv977. In addition, following open science initiatives (Munafò et al., 2017), all raw data, stimuli, and analysis code for each experiment are available online on the open science framework (https://osf.io/9q5jx/).

We note one minor deviation from the pre-registered analysis. We pre-registered that prior to building regression models, we would remove trials from the data with reaction times less than 10ms, as they are likely to reflect a response error. Due to the type of modelling we performed, which involved shifted log-normal models, low reaction times can make model fitting and model comparison more difficult. As such, the reported models in all experiments have a 100ms cut-off point, rather than a 10ms one. We did run the models both ways and there were no meaningful differences between the models. In fact, there were only a few data points that were between 10ms and 100ms. For example, in Experiment 1, there were only 16 data points in this range out of approximately 16,000 datapoints in total. However, given that the models were easier to work with when using a 100ms cut-off, we chose to use this throughout the experiments.

2.2.2 Participants

One hundred and two participants took part in this study for course credit (21 males. $Mean_{age}$ = 21.09, SD_{age} = 5.30, age range = 18 to 44). All participants provided informed consent before completing the experiment. The experiment was granted ethical approval by the Research Ethics and Governance Committee of the School of

Human and Behavioural Sciences at Bangor University. Participants were excluded if they had an average working memory accuracy that was less than 55% (four participants were removed). Trials with reaction times less than 100ms on the main judgment tasks were also removed. The final sample included 98 participants and a total of 15154 trials.

2.2.3 Stimuli, tasks, and procedure

Art stimuli. The art stimuli dataset consisted of 80 images of representational paintings depicting either human bodies (40 images) or landscapes (40 images). The stimuli were validated previously across a range of dimensions: familiarity, aesthetic appreciation, implied dynamism, and evocativeness (Bara et al., in press). The images were characterised by a realistic representational style in the 19th-20th century European and American pictorial tradition. Each group (landscape or people) was divided further into static and dynamic. Overall, the stimuli were split into four different groups within a 2 (painting type: landscape or people) by 2 (dynamism: static vs. dynamic) design. Each image was cropped to be 785 x 774 pixels in size. For a complete description of the stimuli used in Experiment 1, including the list of artworks, artists, year of production, museum collection, see the Supplementary Materials. Copyright permitting, all the art stimuli that we used are also available on our open science framework page (https://osf.io/9q5jx/). An example of stimuli used across all experiments can be visualised in Figure 1.

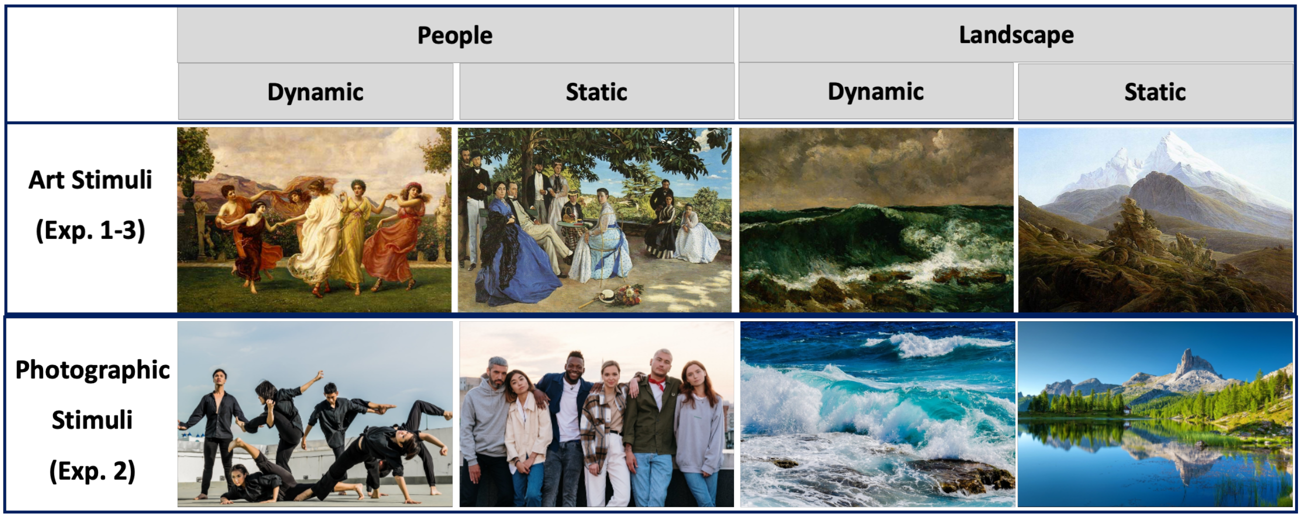


Figure 1. A representation of the four different stimulus categories used in Experiment 1, 2 and 3: people dynamic (N=20), people static (N=20), landscape dynamic (N=20), landscape static (N=20) across art images and non-art images

Tasks and procedure. The main experimental task involved completing a working memory task and a 2-alternative forced-choice (2-AFC; Figure 2). The 2-AFC task consisted of the simultaneous presentation of two paintings next to each other (in the middle of the screen) and participants had to make an aesthetic judgment or an implied motion judgment. In the aesthetic judgment task, participants had to choose which of the two paintings was more aesthetically pleasing, whereas, in the motion judgment task, participants had to indicate which of the two paintings was more dynamic. We chose a motion judgment task as a comparison task condition because of the evidence to suggest that aesthetic judgments involve more elaborate cognitive processes than motion judgments (Chatterjee & Vartanian, 2014; Graf & Landwehr, 2015; Leder et al., 2004; Leder & Nadal, 2014; Beauchamp et al., 2002; Mather et al., 1992; Maunsell & Van Essen, 1983), and thus they may rely on a distinctive set of executive systems that we could probe using a dual-task paradigm.

For both aesthetic judgment and motion judgment tasks, the stimuli were randomly paired from within the same category, across four categories: landscape dynamic, landscape static, people dynamic, people static. Therefore, there were four possible pairing trial types for each judgment type. For example, an aesthetic judgment trial could consist of the pairing of two landscape dynamic paintings, two landscape static paintings, two people dynamic paintings or two people dynamic paintings. Individual paintings could not be paired together on the same trial, although paintings from the same category could be presented more than once, but in a different position of the screen (left versus right). The experimental tasks were produced in PsychoPy (v2020.2.3, Peirce et al., 2019) and run online using Pavlovia and recruitment was via the Bangor University SONA system.

The concurrent working memory task involved the presentation of either one letter (low load condition) or six letters (high load condition) in the centre of the screen. The letters for each trial were presented in a circular arrangement and were randomly selected from a set of ten capital letters (FHKLMTVWYX). No letters were presented twice within the same high load trials. For the low load trials, the space of the other missing five letters was replaced by five dots in a circular array.

Before each experimental task (aesthetic judgment and motion judgment), participants completed a practice block of 32 trials containing both the working memory task and experimental tasks. To avoid a familiarity effect, the art images presented in the practice block differed from the art images in the main experimental tasks. Moreover, the practice block art stimuli had the same characteristics as the art images in the main experimental block – realistic representational 19th -20th Century pictorial style, divided into two main categories landscape (dynamic and static) and people (dynamic and static).

As shown in Figure 2, each trial started with a fixation cross for 1 second (sec) followed by a memory set of either one (low load) or six (high load) letters in the middle of the screen for 2 sec. The participants were instructed to memorise the presented letters to the best of their ability. Next, two paintings (0.5, 0.5 - PsychoPy unit size display, where 1 unit is equal to the height of the screen on which the experiment was running) were presented concurrently at -0.3 PsychoPy units to the left and 0.3 PsychoPy units to the right of the centre of the screen. The two paintings were presented for 2 sec alongside the question "more aesthetic?" or "more dynamic?" at the top of the screen. The paintings remained on the screen for 2 sec while participants were asked to make a speeded aesthetic judgment or a motion judgment by pressing down on either "j" for choosing the left painting or "k" for choosing the right painting. After the participants responded to the 2-AFC task, the memory probe letter was then presented. Participants had to press either the "e" or "d" key to indicate whether the letter was present or absent at the beginning of each trial. The memory probe letter was displayed for 2 sec while the participants had to make a response.

Overall, the experiment consisted of 160 trials, with six trial types formed by intersecting load type (high or low), with image type (landscape or people) and with judgment type (aesthetic judgment or motion judgment). The aesthetic judgment and motion judgment tasks were counterbalanced across all participants so that respondents would start with either an aesthetic judgment task or with motion judgment task.

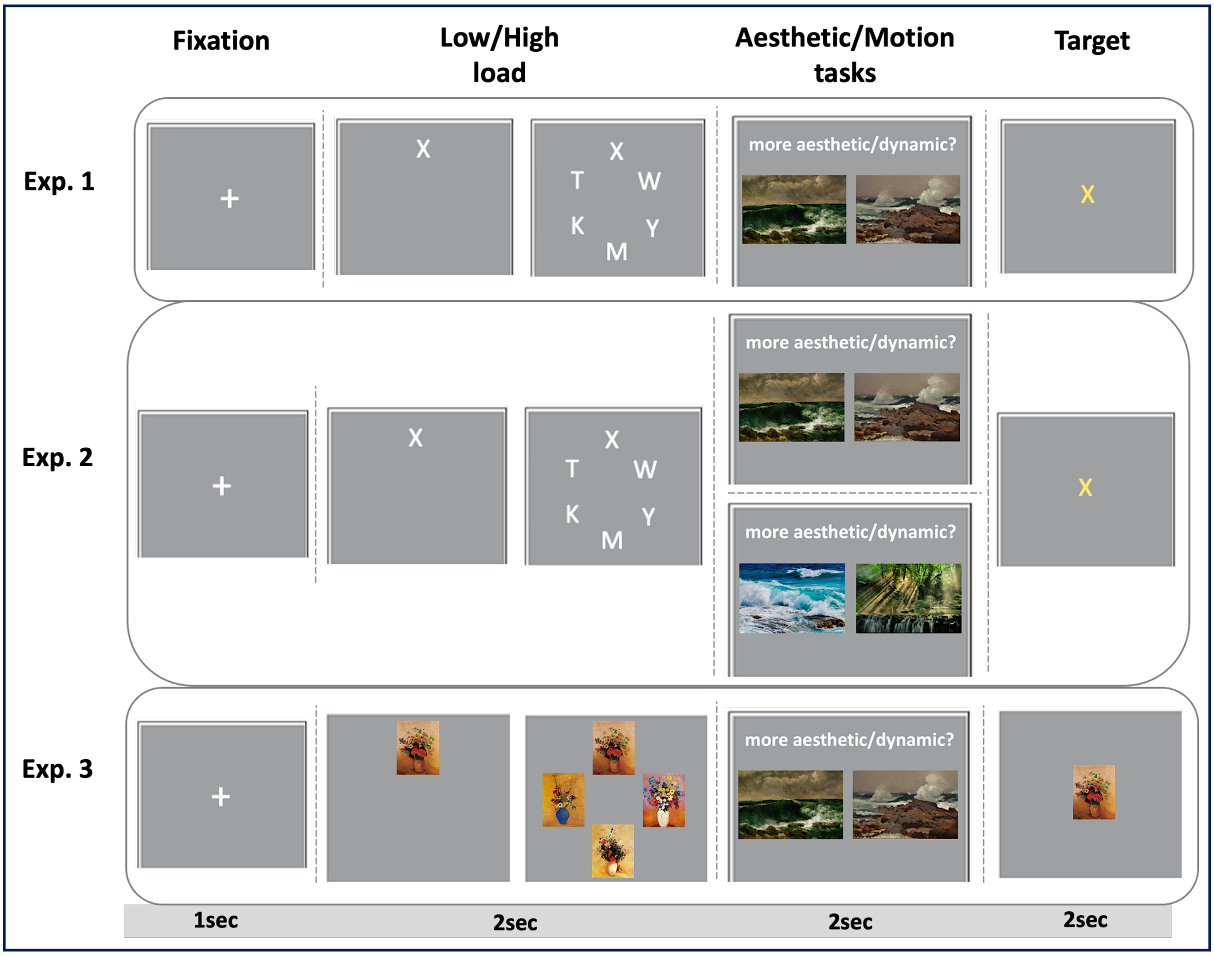


Figure 2. Example of experimental design and stimuli across experiment 1, 2 and 3. Each experiment had the same structure. First, there was a fixation cross, then there were letters or artworks to be held in memory (one item as low load, or multiple items as high load). While memorising the cognitive load content for a later probe, participants responded to 2-AFC aesthetic judgment task or motion judgment task. Following the 2-AFC aesthetic judgment or motion judgment task, a target appeared, and participants had to confirm whether the item was present or absent at the beginning of the trial.

2.2.4 Data analyses

We preregistered a Bayesian estimation approach to multi-level regression modelling (McElreath, 2020). The main rationale was to estimate parameters of interest in multi-level models and perform model comparison between simpler and more complex models. Therefore, when interpreting the findings, we used two approaches. First, we reported and discussed the posterior distribution of our key parameters of interest within the most complex model. Second, we performed model comparison via efficient approximate leave-one-out cross validation (LOO; (Vehtari et al., 2017). LOO is a way of estimating how accurately the model can predict out-of-sample data. Therefore, we took all the models and estimated how accurate they were at predicting the out-of-sample data. In this way, we could estimate how much increasing model complexity increases model accuracy.

More specifically, we followed a recent translation of McElreath's (2020) general principles into a different set of tools (Kurz, 2020), which use the Bayesian modelling package 'brms' to build multi-level models (Bürkner, 2017, 2018). Moreover, our data wrangling approach follows the 'tidyverse' principles (Wickham & Grolemund, 2016) and we generate plots using the associated data plotting package 'ggplot2', as well as the 'tidybayes' package (Kay, 2020). All of these analytical approaches were performed in the R programming language.

Given that the primary dependent variable is reaction time, we modelled the data using a shifted log-normal regression model, which has previously been shown to be a particularly suitable way to model reaction times (Haines et al., 2020). Following the "keep it maximal" approach to multi-level modelling (Barr et al., 2013), we included the maximal number of varying effects that the design permitted. As such, varying intercepts and effects of interest were estimated for participants and stimulus items when possible.

We computed 9 models, which built incrementally in complexity. We first computed two intercepts-only models, just so that we could compare subsequent models that included predictors of interest to models without any predictors. Model b0 included varying intercepts for participants and stimulus items, whereas model b0.1g additionally included a varying non-decision time (ndt) parameter per participant. We then added predictors for task (b1) stimulus type (b2) and load (b3). Two-way interactions between task*type (b4.1), task*load (b4.2) and type*load (b4.3) were then added in further models. Model b5 was the full model, which additionally included the three-way interaction between task, type and load.

Factors were coded according to a deviation coding style, where factors sum to zero and the intercept can then be interpreted as the grand mean and the main effects can be interpreted similarly to a conventional analysis of variance (http://talklab.psy.gla.ac.uk/tvw/catpred/). As such, task, type and load were coded as -0.5 (motion / landscape / low) and 0.5 (aesthetic / people / high).

We set priors using a weakly informative approach (Gelman, 2006). The priors used throughout all three experiments are provided in Table 1. Weakly informative priors differ from uniform priors by placing a constrained distribution on expected results rather leaving all results to be equally likely (i.e., uniform). They also differ from specific informative priors, which are far more precisely specified, because we currently do not have sufficient knowledge to place more specific constraints on what we expect to find. Also, by using weakly informative priors, we allow for the possibility of large effects, should they exist in the data (Gelman, 2006; Gelman & Hill, 2007; Gelman et al., 2013; Lemoine, 2019). Moreover, a further advantage of weakly informative priors is that we would not expect the choice of prior, as long as it remained only weakly informative, to matter too much because the data would dominate the structure of the posterior distribution. The formula for the full model (model 5) is specified here:

```
afc_rtms ~ 1 + task * type * load +
        (1 + task * type * load | pID) +
        (1 + task | item_left) +
        (1 + task | item_right),
        ndt ~ (1 | pID))
```

Note: afc_rtms = alternative forced choice reaction time in milliseconds; task = judgment type (motion vs. aesthetic); type = image category (landscape vs. people); load = low vs. high; pID = participant unique identifier; item_left = image presented on the left side during alternative forced choice trials; item_right = image presented on the right side during alternative forced choice trials; ntd = non-decision time.

Table 1. ***Weakly informative priors used across all three experiments***

Prior	**Class**	**dpar**
normal (6.68, 0.5)	Intercept	
normal (5.70, 0.5)	Intercept	ndt
normal (0, 0.05)	b	
normal (0, 0.1)	sd	
normal (0, 0.1)	sd	ndt
normal (0, 0.1)	sigma	
lkj (2)	cor	

Note: dpar = distributional parameter; ndt = non-decision time; b = population-level or fixed effects; sd = standard deviation; cor = correlation.

Although we pre-registered an approach that built models towards the "maximal" model (Barr et al., 2013), two specific parameters were of particular interest in reference to evaluating our key hypothesis. First, we expected an overall effect of load on reaction time interference in the 2-AFC task, such that there would be greater interference for high than low load. This would suggest that mental operations required during the main task are relatively resource-intensive rather than resource-light, and reliant on controlled and effortful processes. Second, the task*load interaction term was key to evaluating our main hypothesis. Evidence in favour of a specialised cognitive architecture for aesthetic judgments would be provided by a largely positive interaction term, such that the effect of load (high > low) would be greater for aesthetic than motion judgments. In contrast, evidence in favour of a largely general cognitive architecture for aesthetic judgments would be provided by an interaction term that largely overlaps with zero, such that the effect of load (high > low) is largely similar for aesthetic and motion judgments.

2.3 Results

2.3.1 Working memory. Results indicated slower reaction time responses for high load conditions compared to low load conditions (Mean difference = 150ms, 95% CI [130, 180]). Also, we found lower memory accuracy for high load conditions compared to low load conditions (Mean difference = 17.43% accuracy, 95% CI [15.48, 19.39]). For more details, please see Supplementary Figure S3.

2.3.2 2AFC task. Reaction time responses for the 2AFC task are visualised in Figure 3. Visual inspection shows longer reaction time responses on high rather than low load conditions, and longer reaction times when judging art images that contained people rather than landscapes.

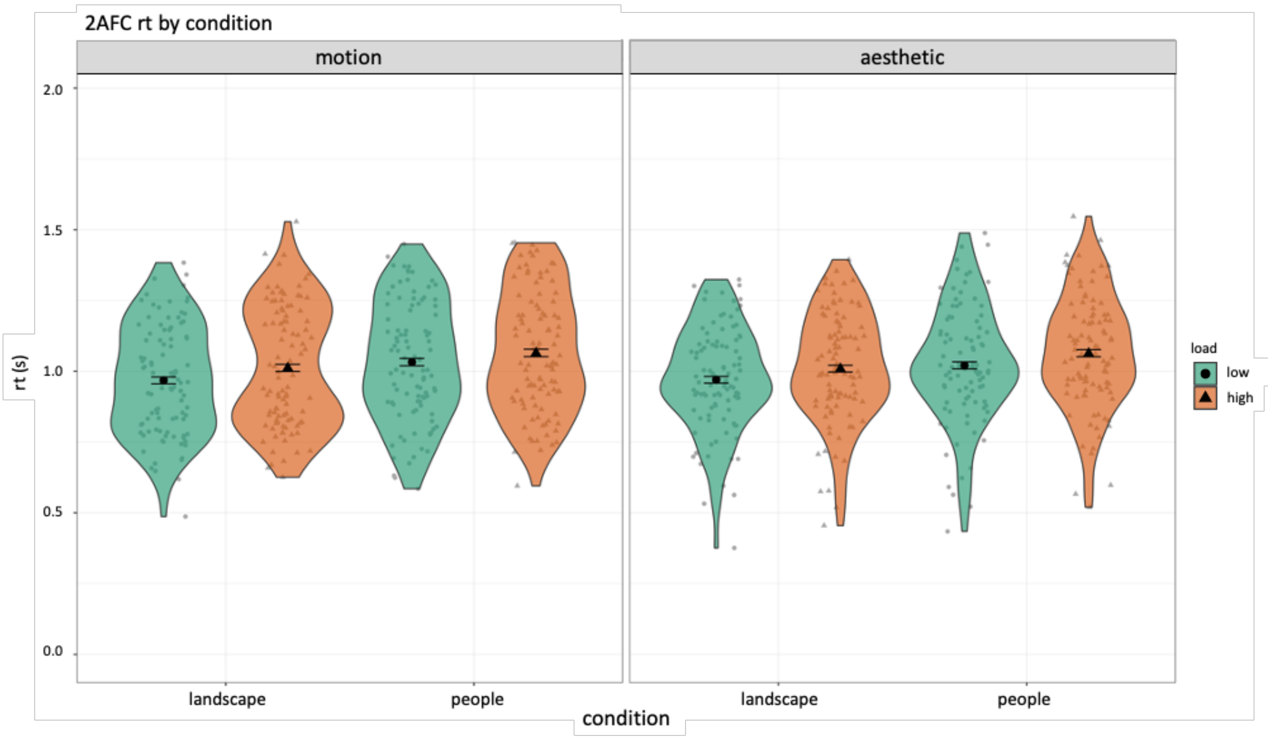


Figure 3. Results for Experiment 1 - Violin plots on summary data showing 2AFC reaction time. Reaction time is reported in seconds (s). The left panel shows reaction times for motion judgment task on low and high conditions for both landscape and people. The right panel shows reaction times for aesthetic judgment task on low and high conditions for both landscape and people. Error bars represent 95% confidence intervals. The black markers (circles or squares) and interval estimates represent the group mean average, whereas the grey markers (circles or squares) represent the individual participants.

Parameter estimates for the most complex model (Model 5) are shown in Figure 4 and Table 2. The posterior distribution for the main predictors indicated a largely positive response for the effect of image type (people versus landscape) and for the effect of load (high versus low). These results show that reaction times were slower for people than landscapes and high versus low load conditions. As can be seen in Supplementary Figure S1, the model estimates for these effects in reaction times are approximately 50msec for the effect of type and 40msec for the effect of load. The distribution of parameter estimates for all interactions effects peaked around zero with values either side of zero emerging as the best estimate of such effects. Therefore, these interaction results provide support for similar deployment of executive resources for both aesthetic and non-aesthetic judgments. In other words, the effect of high versus low load on reaction times was similar across manipulations of task type (aesthetic vs. non-aesthetic) and image type (people vs. landscape).

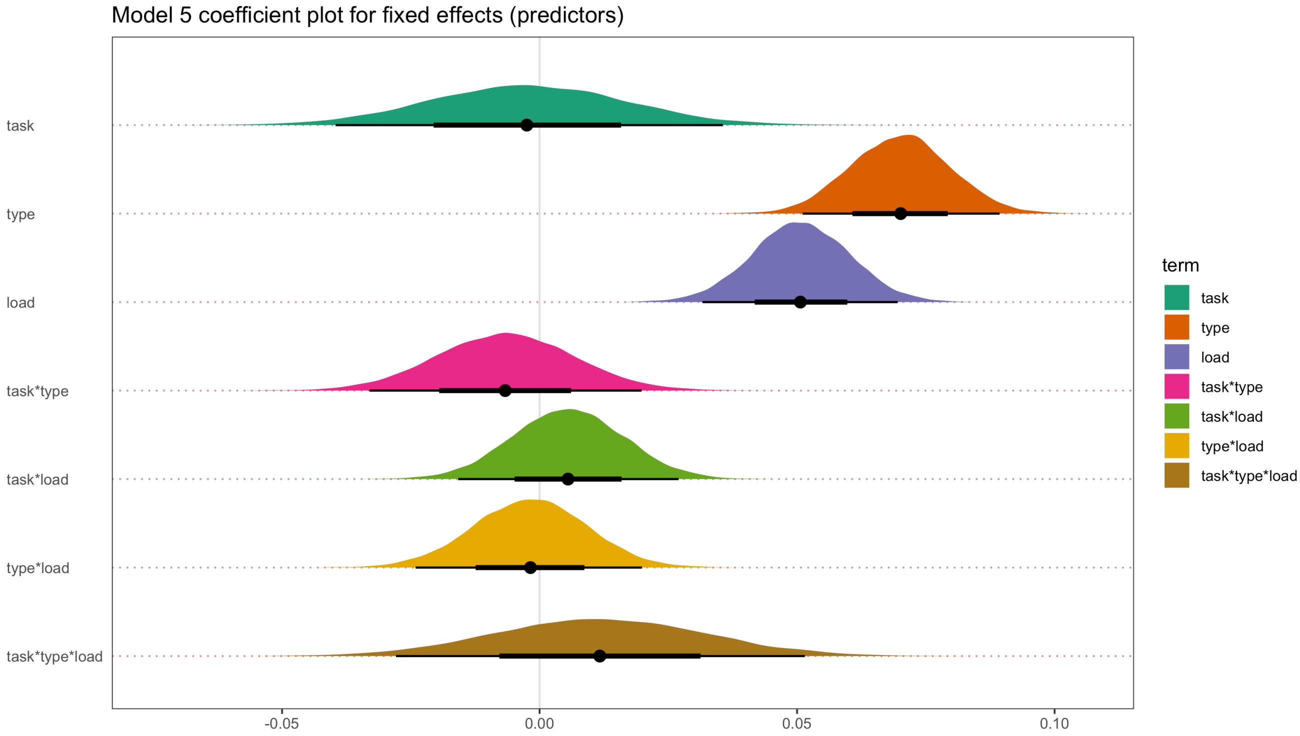


Figure 4. Parameter estimates for each predictor within Model 5. The main predictors that show a clear positive effect are the second and the third predictors, respectively image type and load. The x-axis is expressed on the log(RT) scale. The direct interpretation of these parameters in terms of reaction times is complex as the shifted lognormal model is made of three components. To see estimates of these effects in original units (msec), please see Supplementary Figure S1.
Note: task = judgment type (motion vs. aesthetic); type = image category (landscape vs. people); load = high vs low. Point estimate = median; Error bars represent 66% quantile intervals (thick black lines) and 95% quantile intervals (thin black lines).

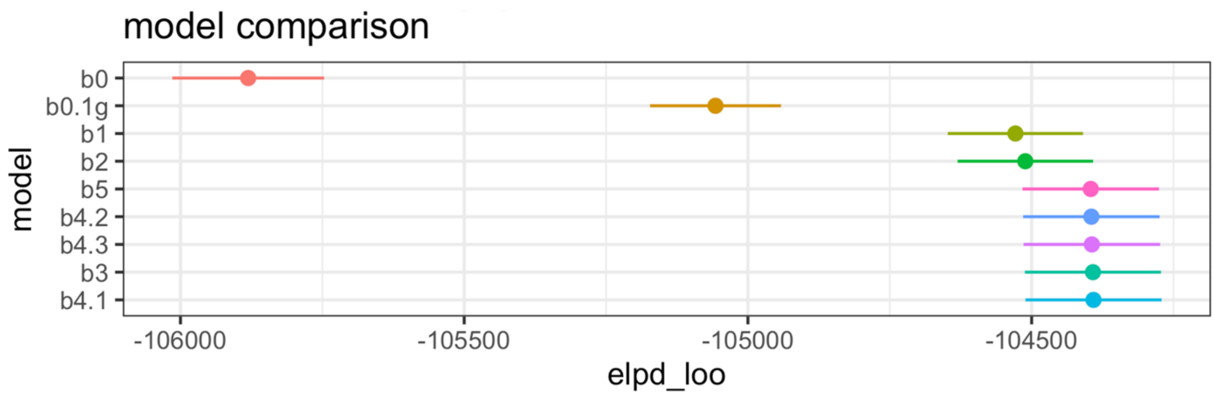
Table 2. Exp. 1, 2 and 3 - Model b5 fixed effects

	Experiment 1			Experiment 2			Experiment 3		
term	***value***	***.lower***	***.upper***	***value***	***.lower***	***.upper***	***value***	***.lower***	***.upper***
Intercept	6.57	6.52	6.61	6.45	6.40	6.50	6.50	6.44	6.56
ndt_Intercept	5.16	4.98	5.34	4.98	4.78	5.18	5.06	4.85	5.27
task	-0.00	-0.04	0.04	0.01	-0.03	0.05	-0.04	-0.08	0.00
type	0.07	0.05	0.09				0.07	0.06	0.09
medium				-0.00	-0.02	0.02			
load	0.05	0.03	0.07	0.04	0.02	0.06	0.03	0.02	0.05
task*type	-0.01	-0.03	0.02				-0.00	-0.03	0.02
task*medium				0.01	-0.01	0.02			
task*load	0.01	-0.02	0.03	-0.00	-0.03	0.02	0.01	-0.02	0.04
type*load	-0.00	-0.02	0.02				0.00	-0.02	0.02
medium*load				0.00	-0.01	0.02			
task*type*load	0.01	-0.03	0.05				-0.01	-0.05	0.03
task*medium*load				-0.02	-0.05	0.02			

Note: ndt_Intercept = non-decision time Intercept; task = motion judgment vs aesthetic judgment; type = landscape vs people; medium (Experiment 2) = photo vs painting; load = low vs high; task*type = interaction between task (motion vs aesthetic) and type (landscape vs people); task*medium (Experiment 2) = interaction between task (motion vs aesthetic) and medium (photo vs painting); task*load = interaction between task (motion vs aesthetic) and load (low vs high); type*load = interaction between type (landscape vs people) and load (low vs high); medium*load = interaction between medium (photo vs painting) and load (low vs high); task*type*load = interaction between task (motion vs aesthetic), type (landscape vs people) and load (low vs high); task*medium*load = interaction between task (motion vs aesthetic), medium (photo vs painting) and load (low vs high).
Experiment 1 and 3 had identical terms. Only Experiment 2 included the term ‘medium’ to describe photo vs paintings. Point estimate = median; Error bars = 95% quantile intervals.

Model comparison analyses are visualised in Figure 5. All models performed better than the intercepts only model (Model b0), as well as the intercepts and varying effects model (Model b0.1g). Error bars for performance of the remaining models all overlapped, suggesting that they performed in a largely similar manner, in terms of out-of-sample predictive accuracy.

Figure 5. Model comparison (1-9 models)



Note: model b0 - included varying intercepts for participants and stimuli; model b0.1 - comprised a varying non-decision time parameter per participant: model b1 – included predictors for task (motion vs aesthetic); model b2 – included predictors for stimulus type (photo vs painting); model b3 – included predictors for load (low vs high); model b4.1 – included interaction between task and type; model b4.2 – included interaction between task and load; model b4.3 – included interaction between type and load; model 5 - full model which additionally included the interaction between task, type and load; elpd_loo = estimate of the expected log pointwise predictive density; loo = leave-one-out estimated cross validation; Error bars = standard error of the mean.

2.4 Discussion

Experiment 1 demonstrated that a cognitively demanding secondary task led to indistinguishable levels of reaction time interference during aesthetic and implied motion judgments. In terms of our main hypothesis, therefore, we provide initial evidence to suggest that, at least in some circumstances, aesthetic and motion judgments may rely to a similar degree on operations of the central executive. However, before drawing firmer conclusions regarding the nature of cognitive processing during aesthetic judgments, we first consider one limitation of these findings. The aesthetic and non-aesthetic judgments were restricted to art stimuli only. Given that previous work has shown that the distinction between art and non-art stimuli can become more salient when paired together (Vessel et al., 2018), it may be possible to reveal evidence for the reliance on a more distinct cognitive architecture by contrasting art stimuli to naturalistic photographs.

3. Experiment 2

3.1 Introduction

Experiment 2 investigated the extent to which higher cognitive load produces greater reaction time interference in aesthetic judgments compared to implied motion judgments, especially whilst viewing artworks rather than naturalistic photographs. We reasoned that by contrasting art to non-art stimuli, we may increase the saliency of the art versus non-art distinction (Vessel et al., 2018), which could make interference effects more pronounced for aesthetic than motion judgments. Additionally, neuroimaging meta-analyses have demonstrated that the aesthetic response to artworks, but not naturalistic photographs, engages additional brain areas such as the amygdala (Boccia et al., 2016) and anterior medial prefrontal cortex (Chuan-Peng et al., 2020), which suggests that more elaborate processing takes place when viewing artworks than photographs.

3.2 Method

3.2.1 Pre-registration. We used the same design and analysis pipeline as in Experiment 1, all of which we pre-registered in advance of the experiment commencing. The pre-registration document for Experiment 2 can be found at https://aspredicted.org/blind.php?x=ah5ub9

3.2.2 Participants

One hundred participants completed this experiment for course credit (16 males. Mean_{age} = 20.09, SD_{age} = 4.94, age range = 18 to 44). All participants provided informed consent before completing the experiment. Participants were excluded if their average working memory accuracy was less than 55% and trials with less than a 100msec reaction time response on the judgment task were also excluded. The final sample included 96 participants and a total of 29946 trials.

3.2.3 Stimuli, task, and procedure

Selection and validation of non-art stimuli. To ensure that naturalistic photographs match the standards of familiarity, aesthetic appreciation, implied motion, and evocativeness previously established for art stimuli, we conducted a separate behavioural stimuli validation experiment (N = 43; 12 males, M_{age} = 20.63, SD_{age} = 3.44). For full results of the stimuli validation experiment, please see supplementary materials (https://osf.io/9q5jx/). In brief, we wanted to investigate the extent to which implied dynamism, evocativeness and familiarity predict aesthetic appreciation. A hierarchical regression model revealed that implied dynamism increased the predictive capacity of the model by 33%, evocativeness by 28%, and familiarity by 14%, suggesting that all predictors of interest had a unique contribution to aesthetic appreciation. Moreover, such results mirror our prior work, which assessed similar types of judgments of the art stimuli used in the current experiments (Bara et al., in press).

The naturalistic photos were obtained from https://www.pexels.com/, a free database containing a diverse range of photos and videos. The photographic stimuli dataset consisted of 80 images depicting either human bodies (40 images) or landscapes (40 images). Each group (landscape or people) was divided further into static and dynamic. Overall, photographic stimuli were divided into four different groups within a 2 (photo type: landscape or people) by 2 (dynamism: static vs. dynamic). In total, therefore, we used 160 stimuli: 80 art images from Experiment 1 and 80 naturalistic photographs. As in Experiment 1, all the stimuli were cropped to be 785 x 774 pixels in size and were presented in colour and with no additional filters to original images. All the naturalistic stimuli that we used in Experiment 2 are freely available on our open science framework page (https://osf.io/9q5jx/). An example of stimuli used in Experiment 2 is visualised in Figure 1.

The tasks used in Experiment 2 were identical to Experiment 1 with a few exceptions (Figure 2). The 2-AFC aesthetic judgment task and motion judgment task consisted of the simultaneous presentation of either two photos or two paintings next to each other in the middle of the screen. The stimuli were randomly paired from within the same category, across eight categories: photos landscape dynamic, photos landscape static, photos people dynamic, photos people static, paintings landscape dynamic, paintings landscape static, paintings people dynamic, paintings people static. Therefore, there were eight possible pairing trial types for each judgment type. For example, an aesthetic judgment could consist of the pairing between of two photos or two paintings from the 'landscape dynamic' category. The same was true for the other seven categories. Individual photographic images or paintings could not be paired together on the same trial, although paintings from the same category could be presented more than once, but in a different position of the screen (left versus right). Overall, Experiment 2 consisted of 320 trials per participant.

As in Experiment 1, before each experimental task, participants completed a practice block of 32 trials containing both the working memory task and experimental tasks. To avoid a familiarity effect, the images used in the practice block differed from the images used in the main experimental tasks.

3.2.4 Data analyses

We used the identical approach to data analyses as performed in Experiment 1 with one exception. Instead of modelling the type of stimulus (landscape vs people), we modelled the type of medium (photograph vs artwork). As such, the modelling process had the same overall structure as Experiment 1, but one factor was different.

3.3 Results

3.3.1 Working memory. Results showed slower reaction time responses for high load conditions compared to low load conditions (Mean difference = 140msec, 95% CI [120, 150]). Also, we found decreased memory accuracy for high load conditions compared to low load conditions (Mean difference = 17.25% accuracy, 95% CI [15.90, 18.59]). For more details, please see Supplementary Figure S6.

3.3.2 2-AFC task. The 2-AFC reaction time responses are shown in Figure 6. Like Experiment 1, on average, participants took longer to respond to high rather than low load conditions.

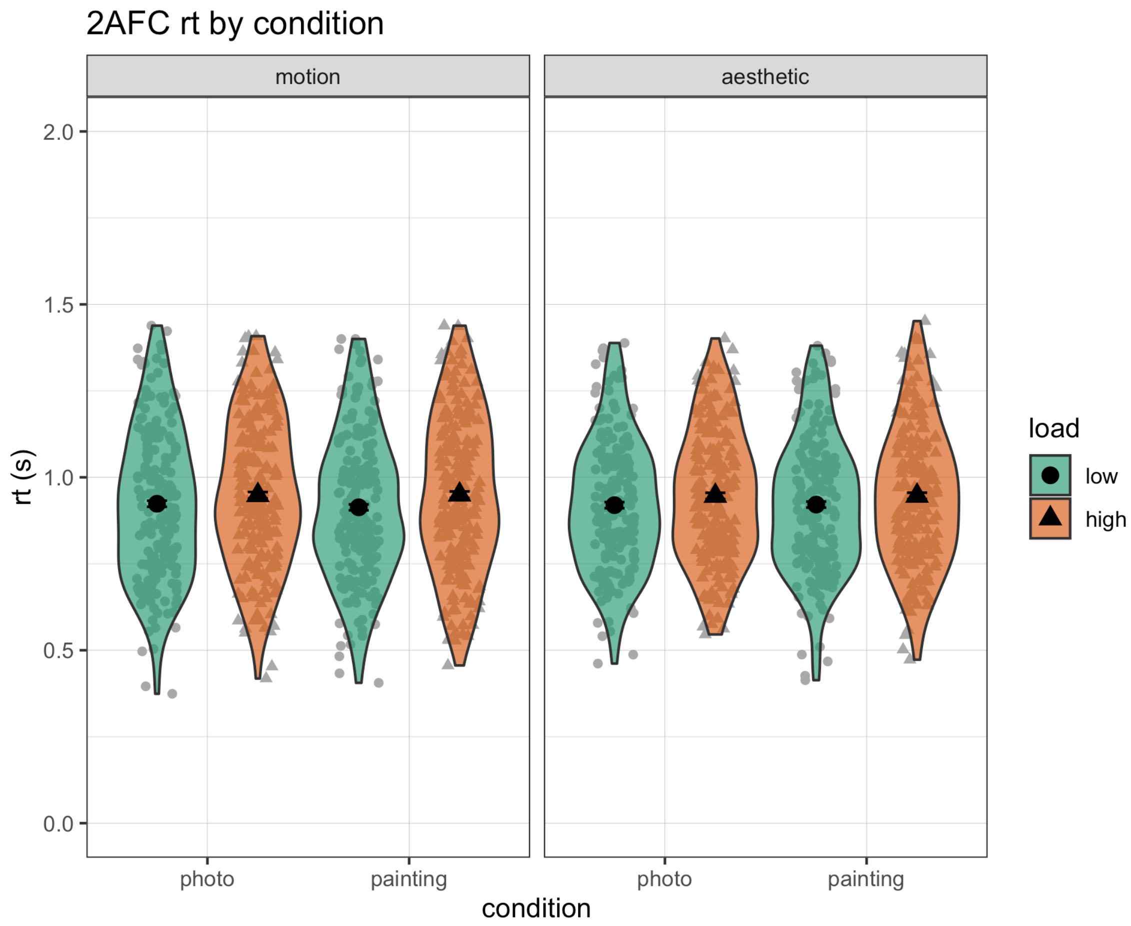


Figure 6. Results for Experiment 2 - Violin plots on summary data showing 2AFC reaction time. Reaction time is reported in seconds (s). The left panel shows reaction times for motion judgment task on low and high conditions for both photos and paintings. The right panel shows reaction times for aesthetic judgment task on low and high conditions for both photos and paintings. Error bars represent 95% confidence intervals. The black markers (circles or squares) and interval estimates represent the group mean average, whereas the grey markers (circles or squares) represent the individual participants.

Parameter estimates for the most complex model (Model 5) are shown in Figure 7 and Table 2. The posterior distribution for the main predictors indicated a largely positive response for the effect of load (high versus low). This result shows that reaction times were slower for the high versus low load condition. As can be seen in Supplementary Figure S4, the model estimates in reaction times are between 20 and 40msec for the effect of load. The distributions for all remaining parameters including all interaction terms showed substantial overlap with either side of zero. These interaction effect results suggest that the effect of high versus low load on reaction times was similar across manipulations of task type (aesthetic vs. non-aesthetic) and medium type (artwork vs. photograph).

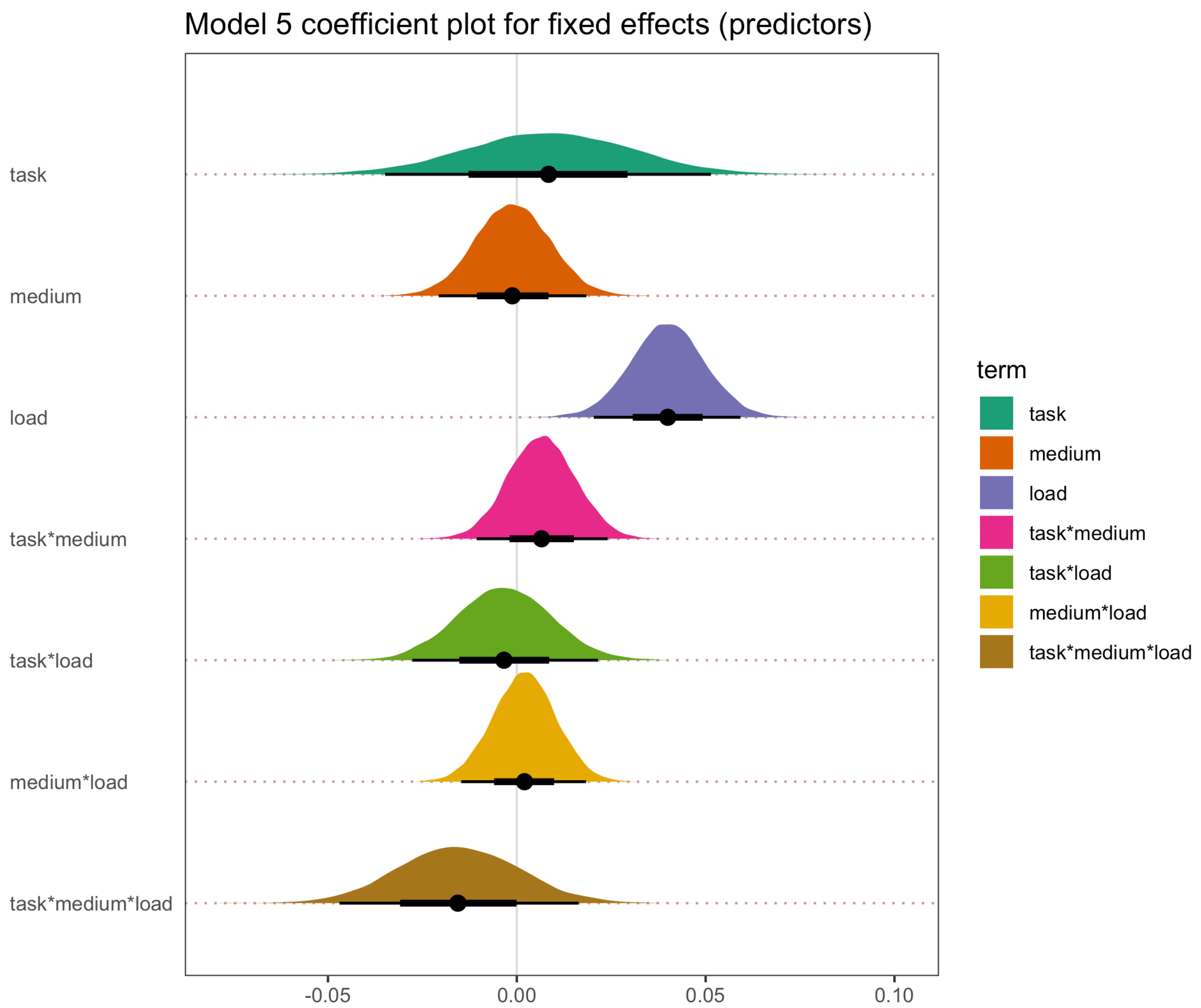


Figure 7. Parameter estimates for each predictor within Model 5. The main predictor that shows a clear positive effect is the load (third predictor). The x-axis is expressed on the log(RT) scale. The direct interpretation of these parameters in terms of reaction times is complex as the shifted lognormal model is made of three components. To see estimates of these effects in original units (msec), please see Supplementary Figure S4. Note: task = judgment type (motion vs. aesthetic); medium = image type (photos vs. paintings); load = high vs low. Point estimate = median; Error bars represent 66% quantile intervals (thick black lines) and 95% quantile intervals (thin black lines).

Model comparison analyses are visualised in Figure 8. All models performed better than the intercepts only model (Model b0), as well as the intercepts and varying effects model (Model b0.1g). Error bars for performance of the remaining models all overlapped, suggesting that they performed in a largely similar manner, in terms of out-of-sample predictive accuracy.

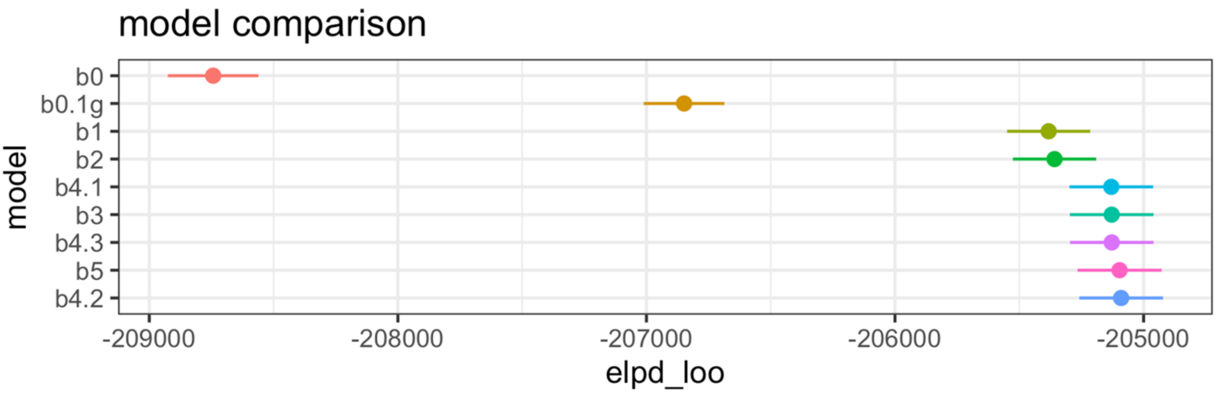


Figure 8. Multivariate model comparison. Models (b1-b5) performed better than the intercepts only model (b0) and intercepts and varying effects model (b0.1).
Note: labels for models (1-9) are similar to Figure 5, except the term stimulus 'type' which has been replaced by 'medium' = photo vs painting.

3.4 Discussion

Experiment 2 showed that the effect of load did not vary by judgment type (aesthetic versus motion) or image medium type (photos and paintings). These findings, therefore, provided further support for the hypothesis that the nature of executive control systems that underpin aesthetic judgments are largely similar as those deployed across a range of distinct judgment types and stimulus types.

In the next experiment, we made additional changes to the experimental procedure, in order to provide a further test of our general hypothesis. In Experiment 3 we modified the content of working memory load from letters to images of visual artworks. By changing the load content, we were able to probe how different aspects of working memory (from verbal in Experiments 1 and 2 to visual in Experiment 3) impacts aesthetic judgments compared to non-aesthetic judgments. Given that image medium variation (photos versus paintings) did not increase the sensitivity to interference effects, in Experiment 3 we used art stimuli only in the main experimental tasks.

4. Experiment 3

4.1 Introduction

In Experiment 3, we addressed the contribution of different modality-specific components of the central executive by changing the content of working memory load. Previous models of working memory have distinguished between verbal working memory, such as the phonological loop, which is responsible for managing speech-based information, and visual working memory, such as the visuospatial sketchpad, which is involved in maintaining and manipulating visuospatial imagery (Allen et al., 2017; Baddeley, 1992; 2012). As such, using letters as working memory content in Experiments 1 and 2 loaded verbal working memory and enabled verbal rehearsal subprocesses to occur. In contrast, in Experiment 3, we used art images as working memory content to load visual working memory and object feature related subprocesses. The main purpose of using paintings instead of letters as load content was to increase the domain overlap between working memory load content and main tasks' stimuli content. We reasoned that increasing domain overlap in terms of art features would make it more likely that interference would be greater for aesthetic than non-aesthetic judgments.

4.2 Method

4.2.1 Pre-registration

We used the same design and analysis pipeline as in Experiment 1 and 2, all of which we pre-registered in advance of the experiment commencing. The pre-registration document for Experiment 3 can be found at https://aspredicted.org/GQE_PSC

4.2.2 Participants

One hundred and one participants completed this experiment for course credit (20 males. $Mean_{age}$ = 21.83, SD_{age} = 4.80, age range = 18 to 43). All participants provided informed consent before completing the experiment. The exclusion criteria were identical to the first two experiments: data files were excluded if an average working memory accuracy was less than 55% and trials with less than a 100msec reaction time response on judgment task were also excluded. The final sample included 97 participants and a total of 15052 trials.

4.2.3 Stimuli, task, and procedure

The stimuli and tasks were similar to Experiment 1 with the following exception: for the working memory load manipulation we used still-life paintings instead of letters (see Figure 2). The high load conditions consisted of the presentation of four still-life paintings in a circular arrangement, whereas the low high load conditions consisted of the presentation of one still-life painting. Participants were informed to memorise the still-life paintings during the retention period and then to indicate whether the memory probe still-life painting was present or absent at the beginning of each trial. The still-life paintings stimuli depicted 10 different vases of flowers by French artist, Odilon Redon (1840-1916). The still-life paintings stimuli that we used for the load content are available on our open science framework page (https://osf.io/9q5jx/).

The match between load content stimuli and main tasks' stimuli content was carefully balanced. In terms of similarities, both load content and main tasks' stimuli content were artworks described by a realistic pictorial style. However, the main difference referred to the subject matter; while the memory load content depicted still life art - vases of flowers, the stimuli in the main tasks described landscape and people in dynamic and static postures.

4.2.4 Data analyses

We used the identical approach to data analysis as performed in Experiment 1.

4.3 Results

4.3.1 Working memory. Results indicated slower reaction time responses for high load conditions compared to low load conditions (Mean difference = 100msec, 95% CI [70, 102]). Also, we found lower memory accuracy for high load conditions compared to low load conditions (Mean difference = 21.42% accuracy, 95% CI [19.52, 23.33]). For more details, please see Supplementary Figure S9.

4.3.2 2-AFC task. The 2-AFC reaction time responses are illustrated in Figure 9. Firstly, on average across participants, a greater response time was observed for high load compared to low load conditions. Secondly, we see that motion judgment took longer time response relative to aesthetic judgment time response.

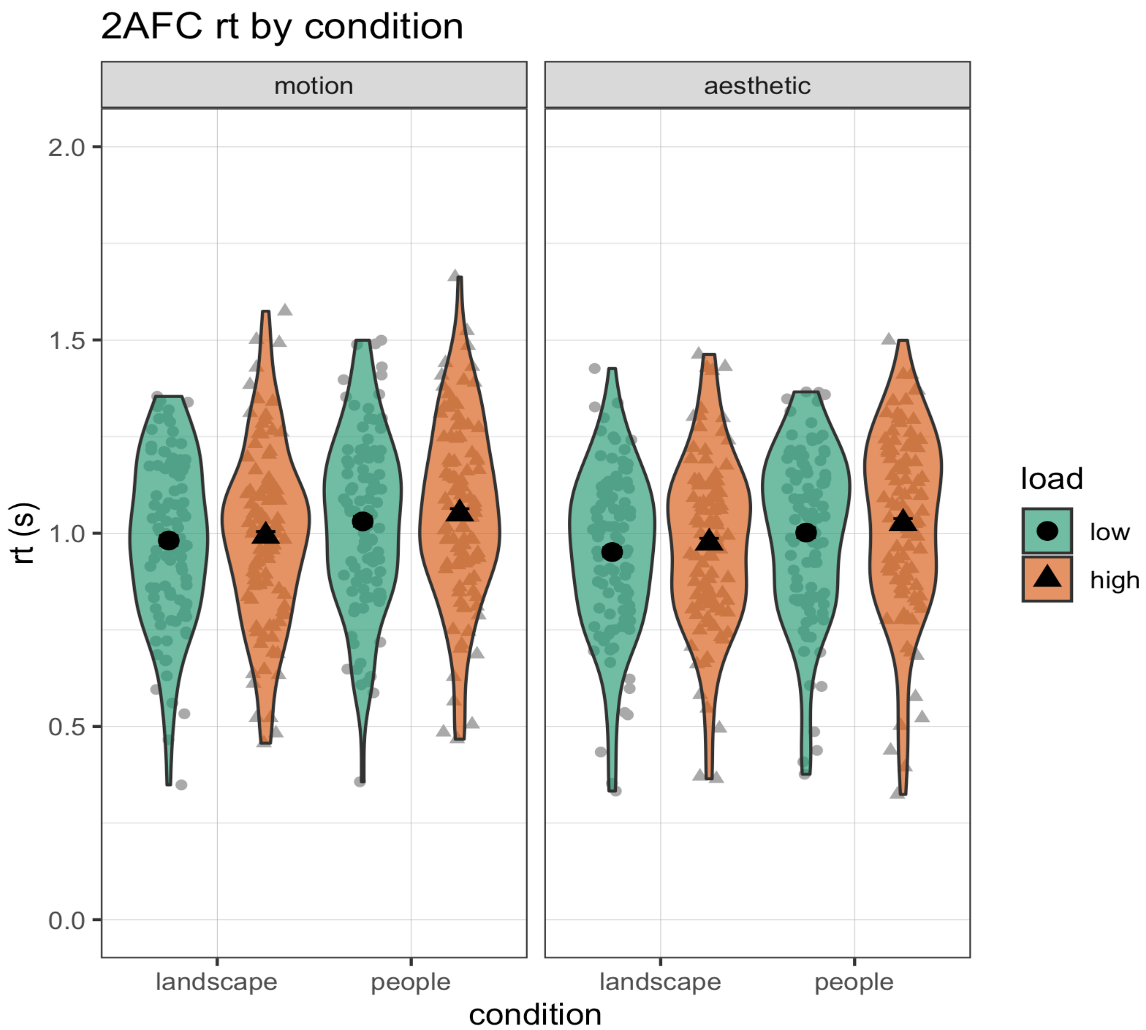


Figure 9. Results for Experiment 3 - Violin plots on summary data showing 2AFC reaction time. Reaction time is reported in seconds (s). The left panel shows reaction times for motion judgment task on low and high conditions for both landscape and people. The right panel shows reaction times for aesthetic judgment task on low and high conditions for both landscape and people. Error bars represent 95% confidence intervals. The black markers (circles or squares) and interval estimates represent the group mean average, whereas the grey markers (circles or squares) represent the individual participants.

Parameter estimates for the most complex model (Model 5) are shown in Figure 10 and Table 2. The posterior distribution for the effect of judgment task showed a clear difference with motion judgments taking longer than aesthetic judgments. In addition, the parameter estimates indicated a largely positive response for image type (people versus landscape) and for the effect of load (high versus low). As can be seen in

Supplementary Figure S7, the model estimates for these effects in reaction times are approximately 60msec for the effect of type and between 10 and 40msec for the effect of load. These results show that reaction times were slower for people than landscapes and high versus low load conditions. In addition, consistent with Experiments 1 and 2, the distributions for the interaction terms all showed substantial overlap with zero. These interaction effect results suggest that the effect of high versus low load on reaction times was similar across manipulations of task type (aesthetic vs. non-aesthetic) and image type (people vs. landscape).

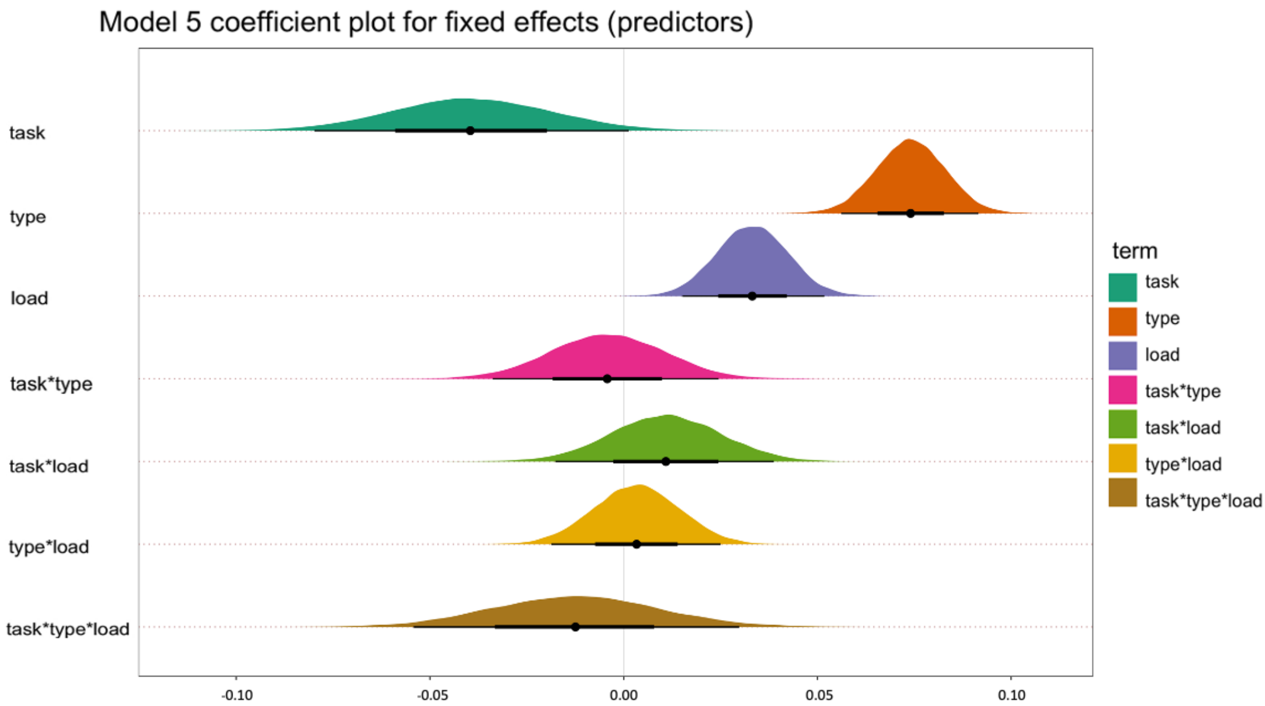


Figure 10. Parameter estimates for each predictor within Model 5. The main predictors that show a clear effect are the task (motion vs. aesthetic), the type of image (people vs. landscape) and the load (high vs. low). The x-axis is expressed on the log(RT) scale. The direct interpretation of these parameters in terms of reaction times is complex as the shifted lognormal model is made of three components. To see the estimates of these effects in original units (msec), please see Supplementary Figure S7.
Note: Point estimate = median; Error bars represent 66% quantile intervals (thick black lines) and 95% quantile intervals (thin black lines).

Model comparison analyses are visualised in Figure 11. All models performed better than the intercepts only model (Model b0), as well as the intercepts and varying effects model (Model b0.1g). Error bars for performance of the remaining models all overlapped, suggesting that they performed in a largely similar manner, in terms of out-of-sample predictive accuracy.

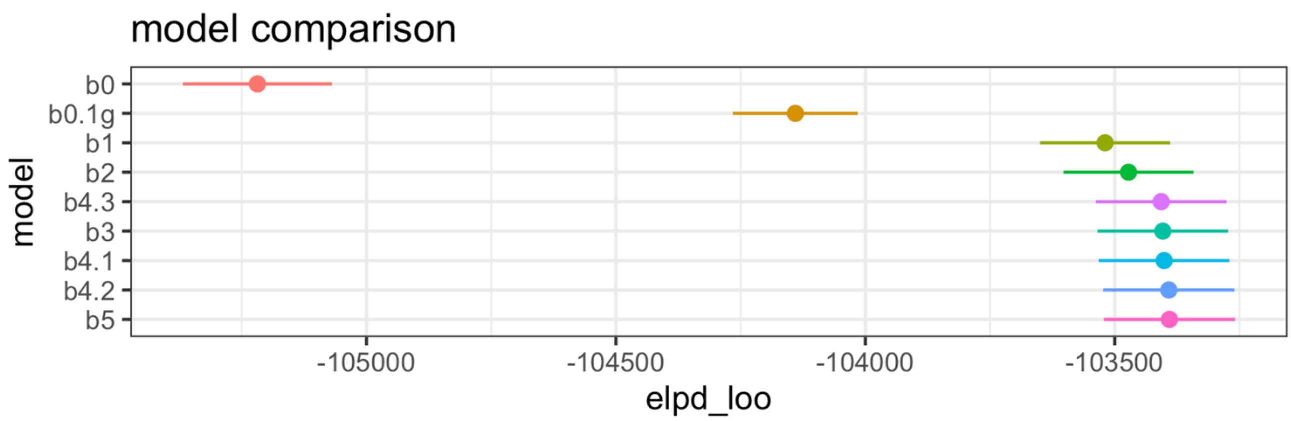


Figure 11. Multivariate model comparison. Models (b1-b5) performed better than the intercepts only model (b0) and intercepts and varying effects model (b0.1).
Note: the labels used for the models (1-9) are similar to Figure 5.

4.4 Discussion

The results from Experiment 3 confirmed and extended the general pattern of findings from Experiments 1 and 2. The primary result showed that even when there is greater feature overlap between load content and the main task (compared to Experiments 1 and 2), there remains a similar deployment of executive control while making aesthetic judgments compared to non-aesthetic judgments.

5. General Discussion

The main objective of the present study was to investigate the extent to which domain-general or domain-specific executive control mechanisms support aesthetic judgments. Across three pre-registered experiments, we found clear evidence that a central working memory load produces similar reaction time interference on aesthetic judgments relative to non-aesthetic (motion) judgments. We also showed that this similarity in processing across aesthetic versus non-aesthetic judgments holds across variation in the form of art (people vs landscape), medium type (artwork vs photographs) and load content (art images vs letters). These findings, therefore, suggest that across a range of experimental contexts, aesthetic and motion judgments rely on domain-general executive control mechanisms, rather than mechanisms that are more specifically tied to aesthetic contexts. In doing so, these findings show a pattern of results that generalises across a range of stimulus features and task conditions and shines new light on the cognitive structures that support aesthetic judgments.

5.1 Extension to dual-task work on aesthetics

The current findings extend prior aesthetics research using dual-task paradigms. Prior work using dual-task paradigms addressed the role of executive control resources across aesthetic contexts only (Brielmann & Pelli, 2017; Che et al., 2021; Mullennix et al., 2013; 2016). In contrast, here we use a dual-task paradigm to compare between aesthetic and non-aesthetic categories of judgment. By finding a similarly-sized effect of load on interference across aesthetic and non-aesthetic judgments, it can be inferred that the degree to which resource-intensive compared to resource-light cognitive processes are deployed are largely the same across aesthetic and non-aesthetic contexts. Taken together, we can see that although variations in aesthetic tasks and stimuli can differentially engage executive resources (Brielmann & Pelli, 2017; Che et al., 2021), our results nonetheless suggest that when contrasting aesthetic to non-aesthetic judgment, such processing may still reflect the operations of a largely general set of executive systems.

5.2 Theoretical impact: Specialised vs generalist accounts of aesthetic experience

Understanding the form and structure of executive control that is deployed during aesthetic judgments has theoretical impact for cognitive models of aesthetic information processing, as well as our understanding of cognition more generally. Reliance on domain-general executive control mechanisms in both aesthetic and non-aesthetic contexts provide empirical evidence for the proposal that the underlying cognitive control mechanisms that support aesthetic appraisal are comparable to those that support general-purpose behaviour (Bara et al., 2021). More generally, these findings provide support for broader theoretical models from social and cognitive neuroscience, which emphasise the role played by domain-general executive systems in information processing (Binney & Ramsey, 2020; Barrett, 2012; Duncan, 2010; Ramsey & Ward, 2020; Spunt & Adolphs, 2017). In contrast, we provide no support for accounts of aesthetic information processing that propose roles for partly distinct mechanisms between aesthetic and non-aesthetic contexts (Goldman, 2001; Guyer, 2005). This, of course, does not imply that there are no aesthetic contexts where specialsied forms of executive control may be relied upon. Instead, we simply show a series of different task contexts and stimulus features, which rely on generalised forms of executive control.

5.3 Limitations and constraints on generality

Due to the nature of the 2-AFC judgment task that we used, which does not include a "correct" answer but instead reflects a personal judgment, it can be difficult to verify the degree to which each button-press accurately corresponds to a true aesthetic or non-aesthetic judgment. In Experiments 1 and 2, for example, the type of task (aesthetic vs non-aesthetic) had no overall impact on reaction times. It is possible, therefore, that participants were not actually making a meaningful judgment in the aesthetic vs motion task, but instead just pressing buttons at an appropriate time. However, in Experiment 3, there was a difference in reaction time responses between tasks, which suggests that distinctive judgments were being made, and yet the primary results remained the same as Experiments 1 and 2. This provides greater confidence that a different judgment was being made, but that it relied on a common form of executive control. Moreover, we have used the same stimuli in previous research, and they led to distinctive judgments (Bara et al., in press). In addition, the observed levels of accuracy on the load task demonstrates that participants were paying close attention to other aspects of the task. On balance, therefore, we feel that we have sufficient evidence to suggest that it is likely that participants were making distinctive judgements between task conditions.

As previously suggested by Simons et al. (2017), it is also important to recognise relevant constraints on the generality of our findings. Even though we find evidence for a generalised form of executive control in the current experiments that operates across a range of stimulus features and task conditions, we cannot rule out that there are distinct forms executive control deployed in other aesthetic contexts. We can only assert that as tested in the current work, there is no evidence for specialised processing. In addition, we acknowledge that executive resources might operate differently across art experts or in naturalistic contexts, such as art galleries. Therefore, of particular interest for future work would be to test how executive control mechanisms operate in aesthetic and non-aesthetic judgments across real-world environments.

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Data sharing statement

The data supporting these findings, the analysis script codes associated with this study analyses and the stimuli are freely available on the Open Science Framework (https://osf.io/9q5jx/).

Conflict of Interest Statement

The authors declare that there is no conflict of interest.

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