The size-weight illusion and beyond: a new model of perceived weight

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Abstract

In the size-weight illusion (SWI), the smaller of two same-weight, same apparent material objects is perceived as heavier. The SWI has proved difficult to explain via traditional Bayesian models, which predict the opposite effect: expected weight from size (smaller = lighter) should be integrated with felt weight, such that the smaller object should be perceptually lighter. Other authors have proposed that weight and density are combined according to Bayesian principles, or that Bayesian models incorporating efficient coding can predict the SWI via 'likelihood repulsion'. These models, however, have been evaluated only under the narrow conditions of typical SWI stimuli. Here we establish a general model of perceived weight for pairs of objects that differ in weight and / or density and / or size by varying amounts. In a visuo-haptic task, participants (N = 30) grasped and lifted pairs of cubes, and reported their perceived heaviness. We report that the SWI occurs even at very small density differences, repudiating the idea that the illusion requires a significant conflict between expected and felt weight. Across all object pairs, perceived weight was well explained by a model (R^2 = .98) that includes a positive influence of both objects' weights and the judged object's density, but a negative influence of the other object's density. Critically, the influence of both densities on perceived weight is strongly modulated by weight difference, being three times as large for zero / small weight differences than large differences. Thus, it is only under the unusual conditions of typical SWI studies that we confuse weight with density to a substantial extent. Unlike existing models, that are inconsistent with our more comprehensive dataset, our model provides a quantitative, accurate and generalised account of weight perception for pairs of objects across various weight and size conditions.

Author summary

Knowing how heavy an object is allows us to grasp and lift it efficiently and without mishaps. Surprisingly, humans make systematic errors when judging the weight of objects of different

size. For example, when two objects differ in size but have identical weight, the smaller object feels heavier. This is the 'size-weight illusion'. The illusion is strong and reliable and occurs even when we know that the two objects actually have the same weight. The size-weight illusion demonstrates that the human perceptual system doesn't work like a weighing scale, but instead takes into account other object features such as size or density, alongside weight. In this paper, we present a model that allows us to predict perceived weight in the size-weight illusion and across a wide range of objects of different weight / size / density, where previous models have failed. Understanding how weight perception works has a wealth of practical applications, including in virtual reality and in the development of prosthetics that provide users with a more naturalistic experience.

1. Introduction

In the well-known size-weight illusion (SWI) (1), participants are typically presented with one large and one small object, apparently of the same material, but in fact of equal weight. On lifting, the smaller object is perceived as heavier than the larger one. The illusion is robust, persisting even when the lifter knows that the objects have equal weight (2,3), and after grasping forces have adapted to the actual weight of the objects (4).

Although the SWI has long been investigated as a means to understanding human heaviness perception, its mechanism remains largely unexplained (for reviews, see (3,5,6)). Early descriptive accounts suggested that the SWI is caused by a contrast / repulsion effect, where the felt weights of the two objects conflict with those predicted by assuming equal density. Other accounts have suggested that the lifter confounds / combines felt weight with other physical features (generally density: (7–9); but also rotational inertia: (10,11).

In 'contrast' or 'violated expectation' accounts it is noted that object size is used as a predictive feature for object weight (12–14). Smaller objects are expected to be lighter than larger objects, particularly when they are apparently made of the same material – that is, of

equal density. Upon lifting, the smaller object is heavier than expected, and this disparity between expectation and sensory evidence is suggested to cause the illusion. Evidence for this conflict between expected and actual weight comes from the forces used to grip and lift the two objects. On initial lifts, participants use more force to lift the larger (expected to be heavier) object than to lift the smaller one (4,15). These misapplied forces have thus been suggested to drive the illusion: the larger object, being lighter than expected, is lifted faster, and vice versa, producing a mismatch between the expected and actual sensory feedback (5,15). However, it has been widely reported that grasping forces adjust to the weight of the object after a few lifts, while the illusion persists (4,16–18)).

Because the illusion is at odds with the perceiver's prior expectations (that the smaller object should be lighter) the SWI has been labelled 'anti-Bayesian' (19,20). The Bayesian framework has successfully described numerous perceptual phenomena in terms of the integration (generally a weighted averaging) of prior expectations with current sensory cues (21–26). In the SWI, however, the Bayesian prediction is that the smaller object will be perceived as lighter than the larger object, given an assumption of equal density for the two objects. Figure 1 illustrates this: Figure 1A represents the stimulus space, with different possible combinations of two stimuli (weight, volume and density log ratio) indicated by the text labels. Figure 1B shows three hypothetical priors on the same axes: The red lines show theoretically sensible priors, given natural statistics: (i) the larger object is heavier and same-density (solid line), or (ii) the larger object is heavier but slightly less dense (dashed line) (see (27). Both of these priors predict the opposite of the empirical SWI (black dots show stimuli, arrowheads give perceived log weight ratio, taken from current study). Note that the empirical SWI involves biases away from the theoretically sensible priors in red, hence the 'anti-Bayesian' label. The green line shows a hypothetical prior (smaller = heavier) that would predict the SWI. However, this prior is implausible, given environmental statistics in which size and weight are positively correlated.

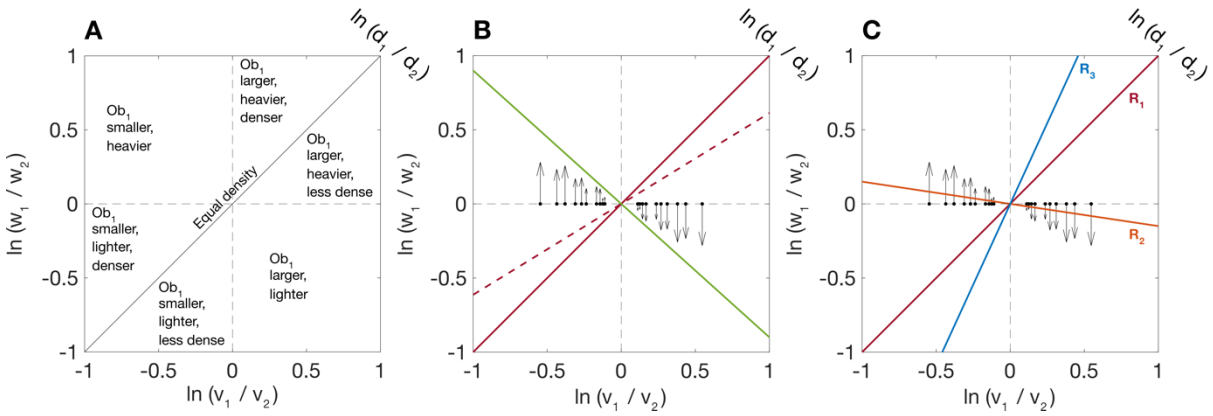


Figure 1 (A) Stimulus space for pairs of stimuli in log-log coordinates, showing log weight ratio and log volume ratio. A value of zero indicates that the two objects have equal weight (or volume). The solid diagonal line indicates equal density, i.e. log density ratio of 0. The labels indicate possible stimulus combinations relating object 1 to object 2. (B) SWI and three hypothetical priors over log volume ratio and log weight ratio. The black dots show SWI stimuli (equal weight but different volume) and arrows show the empirical bias, i.e. the perceived weight ratio, for the same stimuli (data from the current experiment, see below). The green line represents one hypothetical prior (smaller is heavier) that would predict the SWI. In contrast, the red lines show plausible priors in which weight increases with size, as per environmental statistics. (C) Peters and colleagues' (28) model sub-priors, each corresponding to a different density / volume relationship (R); R_1 = equal-density prior; R_2 = smaller is denser and heavier; R_3 = smaller is less dense and lighter. Note that Peters and colleagues represented their priors in terms of log density ratio and log volume ratio; here they are shown in log weight *ratio*, log volume ratio space for a more intuitive representation.

Despite this, Bayesian models of the SWI have been proposed (28,29). Peters and colleagues (28) proposed a Bayesian model that includes three sub-priors over the relationship between the log volume ratio of two objects and their log density ratio (see Figure 1C). Each sub-prior represents a categorical density relationship; R_1: objects have equal density, R_2: smaller objects are denser and heavier than larger ones and R_3: smaller objects are less dense (much lighter) than larger objects. When a typical SWI stimulus pair (e.g. log weight ratio = 0, log volume ratio = 0.5) is encountered, the 'smaller is denser and heavier' prior (R_2 in Figure 1C) dominates, resulting in an illusion (although the priors from Peters and colleagues (28) predict a smaller SWI than reported here). It is not clear whether the model can account for weight perception more broadly as it was only evaluated on pairs of equal-weight objects (i.e., typical

SWI stimuli); predicted biases in weight perception depend on the volume and density ratios of the stimuli and thus which sub-prior dominates perception.

Wei and Stocker (30,31) have suggested that contrast effects analogous to the SWI, i.e. biases away from the prior, can be predicted by Bayesian models incorporating efficient coding of stimulus properties (32,33). Wei and Stocker note that when efficient coding maximises Fisher information (i.e., to reflect the stimulus distribution in the environment), this results in likelihoods that are systematically skewed with a long tail away from the peak of the prior. If a symmetric loss function is also employed (e.g., L2 loss, selecting the mean rather than the maximum of the posterior), estimates will be systematically biased away from the prior, relative to the peak of the likelihood ('likelihood repulsion'), see 'Modelling' section for more detail. Recently, Bays (29) has proposed a Bayesian model of the SWI that incorporates efficient coding and a prior reflecting a positive association between size (volume) and weight. However, Bays' model has only been tested on Peters and colleagues (28) dataset.

Other authors suggest that we are unable to fully separate density and weight (34), or proactively combine them (9). Under these models, denser objects are systematically perceived as heavier. Indeed, heaviness and density estimation appear to be closely related: perceived weight difference increases with increasing density difference weight (34); objects of greater weight are reported as denser (35), and weight difference discrimination is improved when density varies in the same direction as weight (36). Within typical SWI stimuli, weight is kept constant such that density is negatively correlated with volume. Thus, size contributes to the illusion as it is used to infer density ('density-weight-illusion' (7,9,37)).

Wolf and colleagues (8,9) proposed a cue-integration model in which perceived heaviness is a weighted average of two heaviness estimates, one from the object's felt weight and one derived from the object's inferred density. Because denser objects tend to be heavier, the authors suggest that it is adaptive / Bayesian to combine estimates of weight and density when estimating weight to obtain more reliable (less noisy) weight estimates. In the model, the

relative influence of density depends on its relative reliability; when the reliability of (visual or haptic) size information is reduced, density has less effect on the final heaviness estimate (9). In the limiting case, of course, when size information is completely absent (objects lifted via strings / a handle, and no vision), the illusion disappears (9,38,39). It is not clear, however, why we should combine weight and density information in this way, when volume information is available to condition the density-weight relationship. Not only is density a poor cue to weight (when not conditioned on size) but the two estimates will also have correlated noise (thus negating some benefits of integration).

It is well known that the SWI magnitude increases with volume (density) difference (6,28,34,38,40) and this relationship is predicted by all of the above models. SWI demonstrations tend to use fairly large, obvious differences in object volume, in order to obtain a reliable illusion. However, under small conflicts between size-based expectations of weight and direct sensory evidence, these estimates might be integrated; we know that integration occurs for small conflicts but breaks down under conditions of large conflict (41,42) . If integration (the opposite of the SWI) occurs under small conflicts, while the SWI only occurs with large conflicts, this would be broadly in line with the idea that the SWI is driven by violated expectations. This would also be consistent with the effect of the equal density sub-prior in Peters and colleagues model (28). However, integration under small density differences would be at odds with models in which weight and density are confounded / integrated in general (8,9). Furthermore, it is unclear whether humans conflate weight and density in all situations (such as when a smaller object is slightly less dense), or only in the specific and non-accidental conditions of SWI stimuli, when weight is held constant and volume varies.

Here we asked: Can we develop a generalised model of weight perception for varied combinations of size, weight and density? To this end we measured perceived weight for pairs of cubes from a large set in which volume, and / or weight, and / or density were varied in small steps. Size and density were uncorrelated in the full set to prevent learning of unusual size -

weight associations. To preview the main findings: 1) The SWI occurred even at very small size (density) differences, and thus does not rely on large conflicts. 2) Perceived weight was positively correlated with the true weight of both the judged and other stimulus, in addition to the judged object's density. 3) The effect of both objects' densities on perceived weight was strongly modulated by the weight difference between the two objects: three times larger at small / zero weight differences than at large weight differences. In fact, the other object's density had an effect only when the two objects had similar weight, when it was negatively associated with the judged object's perceived weight. Thus, the perceptual system does conflate weight and density, but this effect is much larger in the specific and peculiar conditions of typical studies of the SWI. We provide a model (R^2 = .98) that captures biases in perceived weight in the SWI and across the full stimulus set. In addition, we compare this model to existing models of the SWI, and to a novel efficient-coding Bayesian model of the SWI.

2. Materials and Methods

2.1 Participants

Thirty naïve participants (age *M* 21.4, *SD* 5.6 years) from the University of Southampton Psychology student community took part in the experiment; undergraduate students were compensated for their participation with course credits. All reported normal or corrected-to-normal eyesight and no upper limb impairment. The experiment was approved by the University of Southampton Psychology Ethics Committee; all participants gave prior informed consent.

2.2 Stimuli

Stimuli were 15 plastic cubes (3D-printed in black polylactic acid (Figure 2A–B). Each cube was filled with sand, polystyrene pellets, and / or brass to create the desired volume, weight and density values for the different stimulus sets, depicted in Figure 2A. The centre of mass of the cubes remained at the geometric centre and the filling did not move inside the cubes during lifting. A panel concealed at the bottom kept the appearance homogeneous. Weight was measured with a 0.1 g resolution.

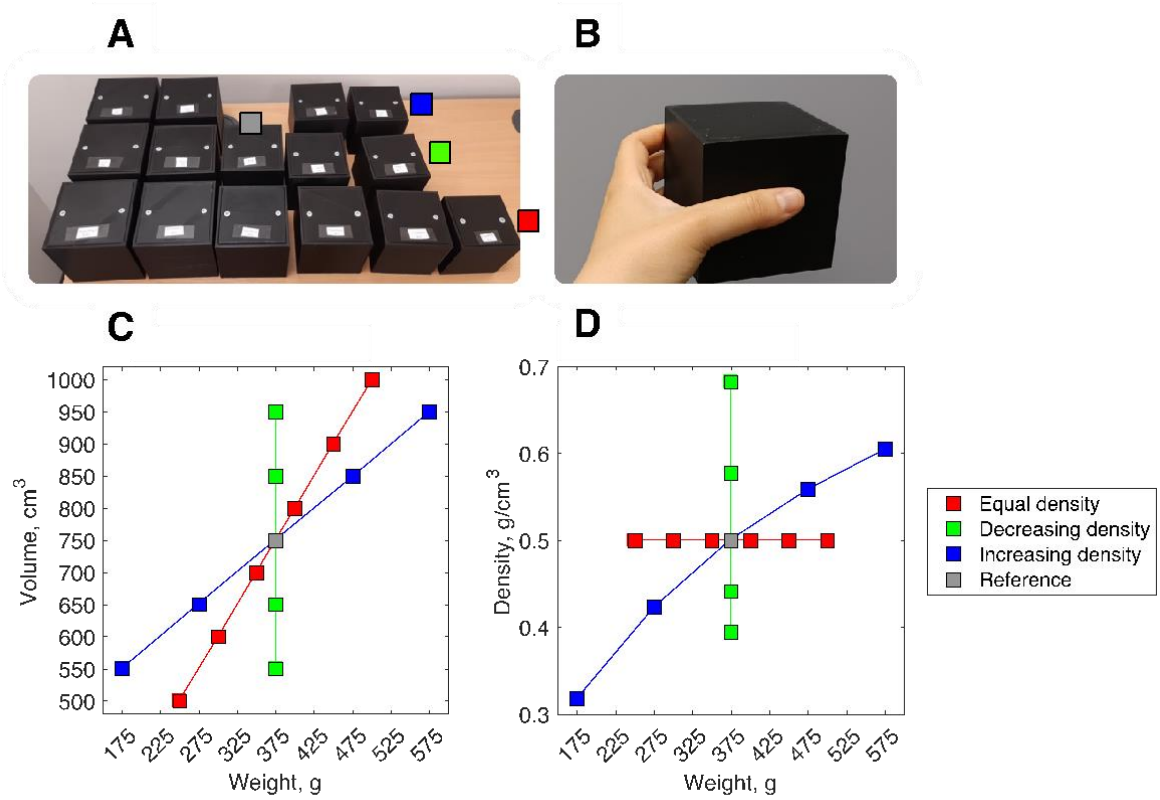


Figure 2 Stimulus set. (A) Full stimulus set, see legend in (D). Note that the stimuli are shown upside-down in the picture. (B) 500 cm^3 stimulus for scale. (C) Stimulus volume as a function of weight. (D) Stimulus density as a function of weight.

The complete stimulus set included three subsets (Figure 2C–D), corresponding to different volume / weight relationships: 1) Equal density (red): weight increased linearly with volume (as for 'normal' same-material objects); 2) Equal weight (green): density decreased with increasing size (typical SWI stimuli); 3) Increasing density with increasing size (blue): both weight and density increased with size. The middle cube (volume, weight, density: 750 cm^3, 375

g, 0.5 g / cm^3) was common to all three subsets. Volumes within each set increased in 100 cm^3 steps, with the addition of 50 cm^3 steps below and above the middle stimulus in the fixed density set. Minimum (maximum) volume, weight, density differences across any stimulus pair were: 50 (250) cm^3, 25 (200) g, 0.02 (0.18) g / cm^3, respectively. Density ratios for stimulus pairs ranged between 0.47–0.97 (less dense / denser stimulus), 0.58–0.89 for equal weight (SWI) stimulus pairs. In comparison, previously reported density ratios (less dense / denser) for the minimal density differences have been: 0.67 (43); Experiment 4); 0.64 (44); 0.52 (38), 0.51 (45), Experiment 1); the largest density ratio tested by Peters and colleagues was 0.42 (28). Larger density ratios were tested by Wolf and colleagues (9): 0.87, in a set of same-volume (increasing density) stimuli. To our knowledge, only Kawai and colleagues (46) investigated smaller differences (density ratio: 0.98), by manipulating the visual size of stimuli lifted via strings in an augmented-reality setting; although they suggest that heaviness perception might be veridical at very small (but still detectable) volume differences, it should be noted that the magnitude of the SWI is expected to be smaller in absence of haptic size cues (38,47) and in virtual environments (48,49).

2.3 Task and trials

Stimuli were presented in pairs. In each trial, participants simultaneously grasped and lifted both cubes in full visuo-haptic conditions, and verbally reported both objects' weights using magnitude estimation. This paired presentation (common in SWI experiments) allowed us to model the perceived weight of each object in addition to the pair's perceived weight difference or weight ratio. Experimental trials included all possible stimulus pairs (same- and different-subset pairs), excluding pairs of identical stimuli. This gave 105 unique pairs and 133 pairs in total (trials including the middle / common stimulus were repeated due to a coding error). Each stimulus pair was presented twice, with left and right position switched between the two trials (266 trials in total). Trials were randomised for each participant.

2.4 Setup

The participant and the experimenter sat at opposite sides of a table covered in thick felt to muffle auditory cues to the objects' weights. Two numbers (1, 2) marked the positions of the stimuli on the table (centre-to-centre distance between stimuli, centre of stimuli to table edge: both 20 cm) and served to remind participants the order in which to report their estimates. A frame-mounted black curtain was used to control stimulus presentation, such that the participant only ever saw the two stimuli of the current trial. A desktop computer running MATLAB (The MathWorks Inc., 2020) was used to randomise stimulus presentation and record participant responses.

2.5 Procedure

The experiment was completed in two identical laboratory sessions on separate days, each lasting 60–90 minutes. At the beginning of each session, participants were presented with the middle cube (750 cm^3, 375 g) as the reference stimulus, and told that this had a weight of '50' (arbitrary units). The reference was presented again every 20 trials. Participants were instructed to look at the stimuli while lifting. Exploration mode was not restricted: participants were free to grasp and lift the cubes as they thought best; they were not restricted to use index and thumb only. This was done to provide the most reliable size estimates (9). Trials were not timed, but participants were encouraged to give an answer if they waited more than 30 seconds (approx.).

3. Results

Participants' magnitude estimates were transformed into grams and then normalised to remove individual differences in how the response scale was used: Each participant's estimates were multiplied by the ratio of their individual grand mean across stimuli to the grand mean across all participants (thus, after normalisation, each observer had the same mean response). Outliers per condition were then removed iteratively: for each object within each

stimulus pair, values more than 5 SDs, then 4 SDs, and 3.5 SDs from the mean across observers were removed (65 datapoints in total, or 0.4%). Data were re-normalised after each iteration. All further analyses were conducted on the resulting dataset.

Weight estimates for within-subset pairs (i.e., both objects from the same subset) are shown in Figure 3, alongside model fits (see below, Equation 1–2). Data have been collapsed across repetitions within participants and *SE* bars show inter-observer variation. We present the perceived weight of the judged object (i.e., the object within each pair whose weight is being reported) in terms of its own properties (weight / density) and the properties (weight / density) of the other object in the pair. Each object in turn was considered the judged object.

For equal density, i.e. 'normal' object pairs (Figure 3A–B), weight estimates were highly correlated with the true weight of the judged object, as expected. However, they were also positively correlated with the weight of the other object (denoted by symbol size in Figure 3A; see the vertical spread corresponding to weight of other object); note that this is an averaging, rather than a contrast effect. Perceived weight difference (perceived 'judged' weight - perceived 'other' weight) was linearly related to stimulus weight difference (Figure 3B; data are symmetrical in all difference plots (B, D, F) as each object in each stimulus pair serves as 'judged').

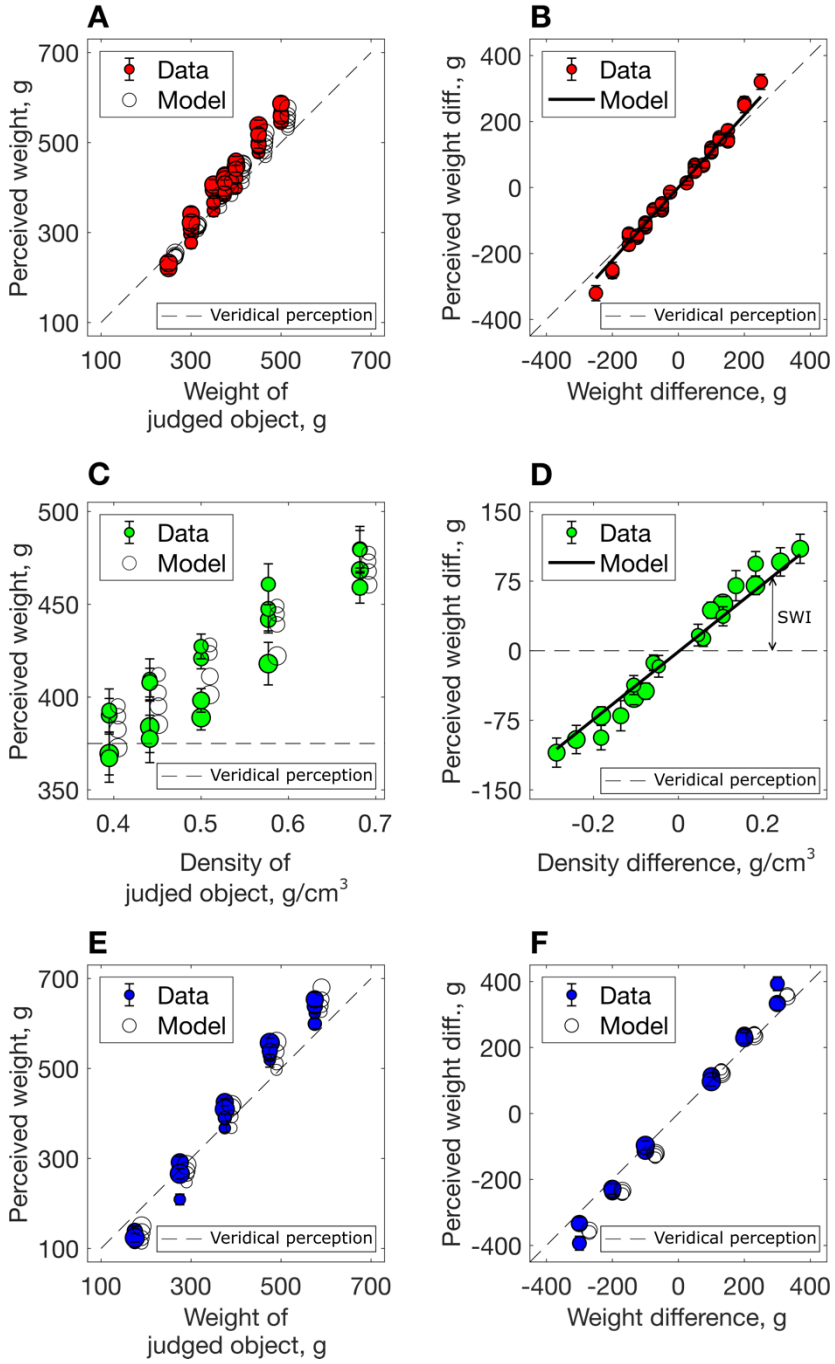


Figure 3 Perceived weight (A, C, E) / weight difference (B, D, F) for within-subset stimulus pairs, averaged across participants; error bars show ± 1 SEM; solid lines / open symbols show the model predictions (described below, Equation 1 and 2); (A, B, E, F) the dashed lines are identity lines. (A–B) Equal density pairs: (A) Weight estimates as a function of stimulus weight; symbol size indicates the weight of the other stimulus in the pair. (B) Data re-expressed as perceived weight difference. (C, D) Equal weight (SWI) pairs: (C) Weight estimates as a function of stimulus density; symbol size indicates the density of the other stimulus in the pair. (D) Perceived weight difference, as a function of density difference; symbol size indicates the average density. (E, F): Increasing density pairs: (E) Symbol size indicates the other stimulus weight; (F) Symbol size indicates the average density.

Weight estimates for the equal weight (SWI) pairs are shown as a function of the judged object's stimulus density (x-axis) and the other object's density (symbol size, Figure 3C). In line with the size-weight illusion, perceived weight was positively correlated with object density: denser (and smaller) stimuli were perceived as heavier (overall positive slope of the data). Perceived weight was also negatively correlated with the other object's density, the judged object appearing heavier when judged next to less dense (larger) objects (see the vertical spread of data points in 3C). The data are re-expressed as perceived weight difference as a function of density difference in Figure 3D. It is clear that the magnitude of the SWI (i.e. deviation from veridical perception) increases with density difference, but still occurs with small density (or volume) differences. Thus, we find no evidence for integration of expected and sensory weight estimates under small conflicts.

Lastly, in the increasing density pairs (Figure 3E), weight estimates were positively correlated with the object's weight, but also correlated with the other object's weight (as in the equal-density pairs; see vertical spread of data in 3E). Figure 3F shows that perceived weight difference increases linearly with true weight difference. In this set, weight (or weight difference) is correlated with density (or density difference); the effect of density contributes to the increased slope of the data, relative to veridical perception (identity line).

Figure 4A summarises results for all trials, including across-subset pairs (i.e. each object in a pair from a different stimulus subset), in a format that illustrates the variable influence of density on perceived weight. For every stimulus pair (represented by a dot), perceived weight difference (y-axis) is presented as a function of stimulus weight difference (x-axis) and stimulus density difference (colour). Lines show the model fit (see Equation 2 below). The overall slope of the data shows the strong relationship between true and perceived weight difference. The vertical spread of the different colours shows the effect of density difference on perceived weight difference. The two are not independent: there is a central 'bulge', where the effect of density is larger (more vertical spread). This plot shows that the effect of density (or

density difference) on perceived weight (or perceived weight difference) is strongly modulated by stimulus weight difference, being much greater for small / zero weight differences. Figure 4B summarises the influence of the two objects' densities on perceived weight, as captured by the model's density coefficients (see below). The conflation of weight and density is dramatically increased under the conditions of typical size-weight stimuli, where weight difference is zero.

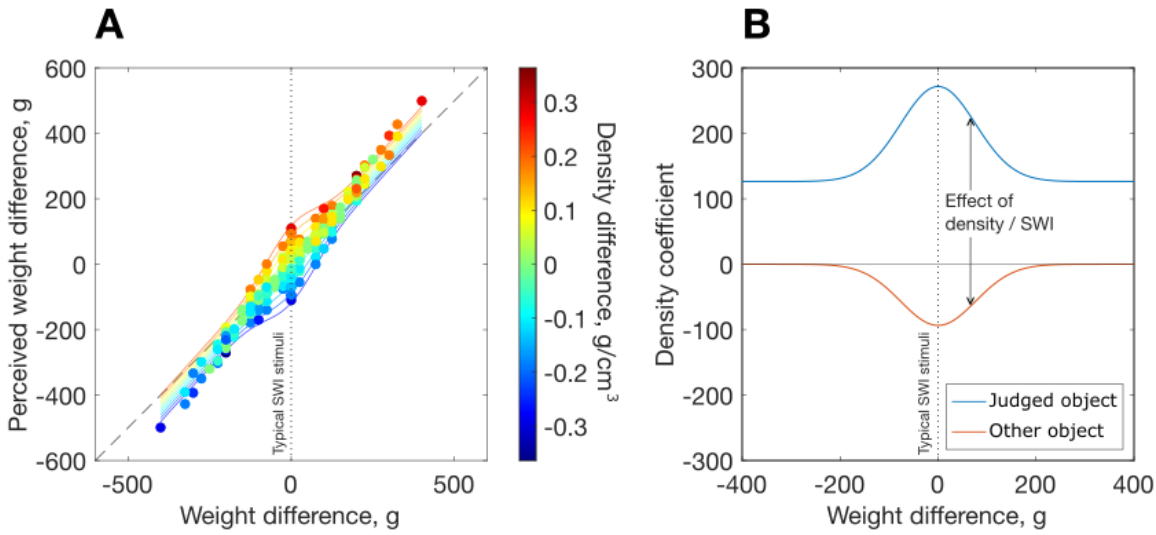


Figure 4 (A) Perceived weight difference as a function of weight difference and density difference in the full dataset. Markers show the data, solid lines show the model predictions (see Equation 2) at equally spaced density differences. The vertical spread of the data with density difference (marker colours) shows the effect of density in typical SWI stimuli (i.e., equal weight: vertical dotted line) and across the full set. The dashed diagonal line shows veridical perception. (B) The influence of density (i.e., density coefficients) as a function of weight difference in the model.

4. Modelling

4.1 Descriptive model

We developed a model to capture perceived weight ($\widehat{w}_1$) for all stimulus combinations, as a function of the weight and density of the judged (w_1, d_1) and other object (w_2, d_2). All analyses were done in MATLAB and optimal coefficients (minimising the summed squared residuals, SSR) were identified via gradient descent. Alternative candidate models are presented in Supplementary Table 1 alongside model comparison statistics. Models including

the objects' volumes (v_1, v_2) instead of density were also tested, see Supplementary Table 2. To prevent over-fitting, we used leave-one-out cross-validation on the normalised dataset, leaving out each participant in turn. The best model (Equation 1) explains 98% of the variance in the full dataset:

$$\widehat{w}_1 = C + \beta_1 w_1 + \beta_2 d_1 + \beta_3 w_2 + \beta_4 d_1 N(|w_1 - w_2|, 0, \sigma^2) + \beta_5 d_2 N(|w_1 - w_2|, 0, \sigma^2) \quad (1)$$

Model predictions for $\widehat{w}_1$ as a function of the observed values are shown in Figure 5B.

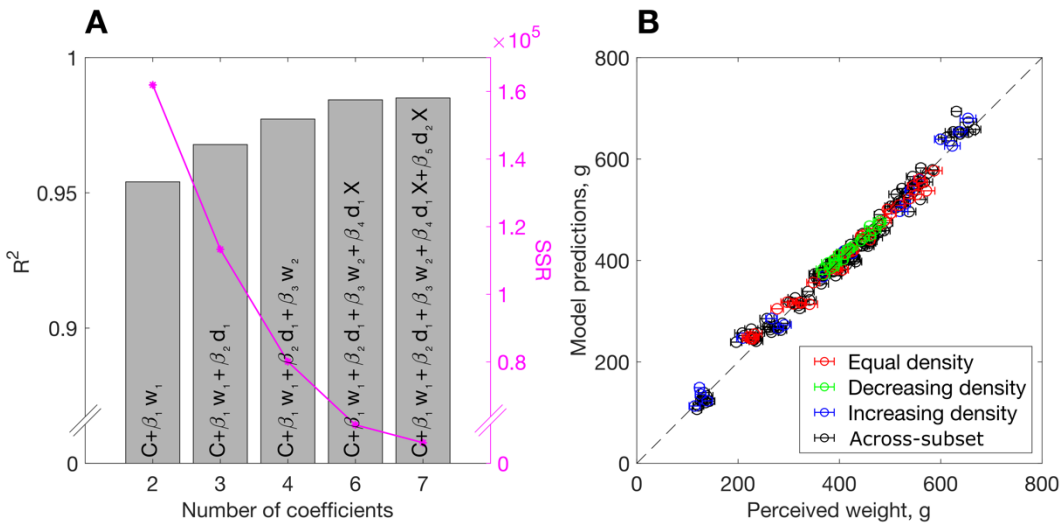


Figure 5 (A) Variance in perceived weight explained by the addition of each predictor in the model (bars) and corresponding SSR (magenta lines and markers). The order of predictors follows the maximum increase in R^2 with each addition (see SI, Table S1); X = $N(|w_1 - w_2|, 0, \sigma^2)$. (B) Predictions of perceived weight from the best-fitting model (Equation 1) as a function of participants' estimated weight for each stimulus, across all object pairs. The dashed line shows equality. Error bars give ± 1 SEM.

Accordingly, the perceived weight difference ($\widehat{w}_1$ - $\widehat{w}_2$) between two stimuli can be predicted via the following equation:

$$\widehat{w}_{diff} = (\beta_1 - \beta_3)(w_1 - w_2) + \beta_2(d_1 - d_2) + (\beta_4 - \beta_5)(d_1 - d_2)\, N(|w_1 - w_2|, 0, \sigma^2) \quad (2)$$

Perceived weight was positively correlated with the object's weight (β_1 = 1.23) and its density (β_2 = 126.43), and with the other object's weight (β_3 = 0.13). However, the influence of density on perceived weight was modulated by weight difference, as captured by the two

Gaussians (see the central 'bulge' in Figure 4A). The density of the judged object positively influenced its perceived weight ($ß_4$ = 27814), whereas the other object's density had a negative influence ($ß_5$ = -2566.2). Sigma for the Gaussian components was 76.44. Figure 4B shows the influence of both objects' densities as a function of weight difference: the combined influence of the two densities on perceived weight was approximately three times larger for zero weight differences than for large weight differences.

4.2 Efficient coding Bayesian ratio model

Traditionally, Bayesian models have been employed to account for perceptual biases towards a prior (i.e. towards the most frequent or probable stimuli). Examples in the literature include biases for light-from above (50), isotropy assumptions when interpreting foreshortening (41), global convexity of surfaces (51), and 'slow and smooth' motion (52). However, as described by Wei and Stocker (30,31), Bayesian models incorporating efficient coding of stimulus features can also predict repulsion biases, i.e. biases *away* from the prior. Given that the SWI (and not integration) is observed even for very small density differences, we asked whether such a model might provide a quantitative, Bayesian model of the SWI as a 'repulsion' effect, where perception is biased away from a prior for equal density. Wei and Stocker (30,31) show that the expected perceptual bias $b(\theta_0)$ for a stimulus value θ_0 from a stimulus distribution θ can be predicted from the prior, p(θ) (in fact from the slope of its squared reciprocal), as in Equation 3:

$$b(\theta_0) \approx C(1/p(\theta_0)^2)' \qquad (3)$$

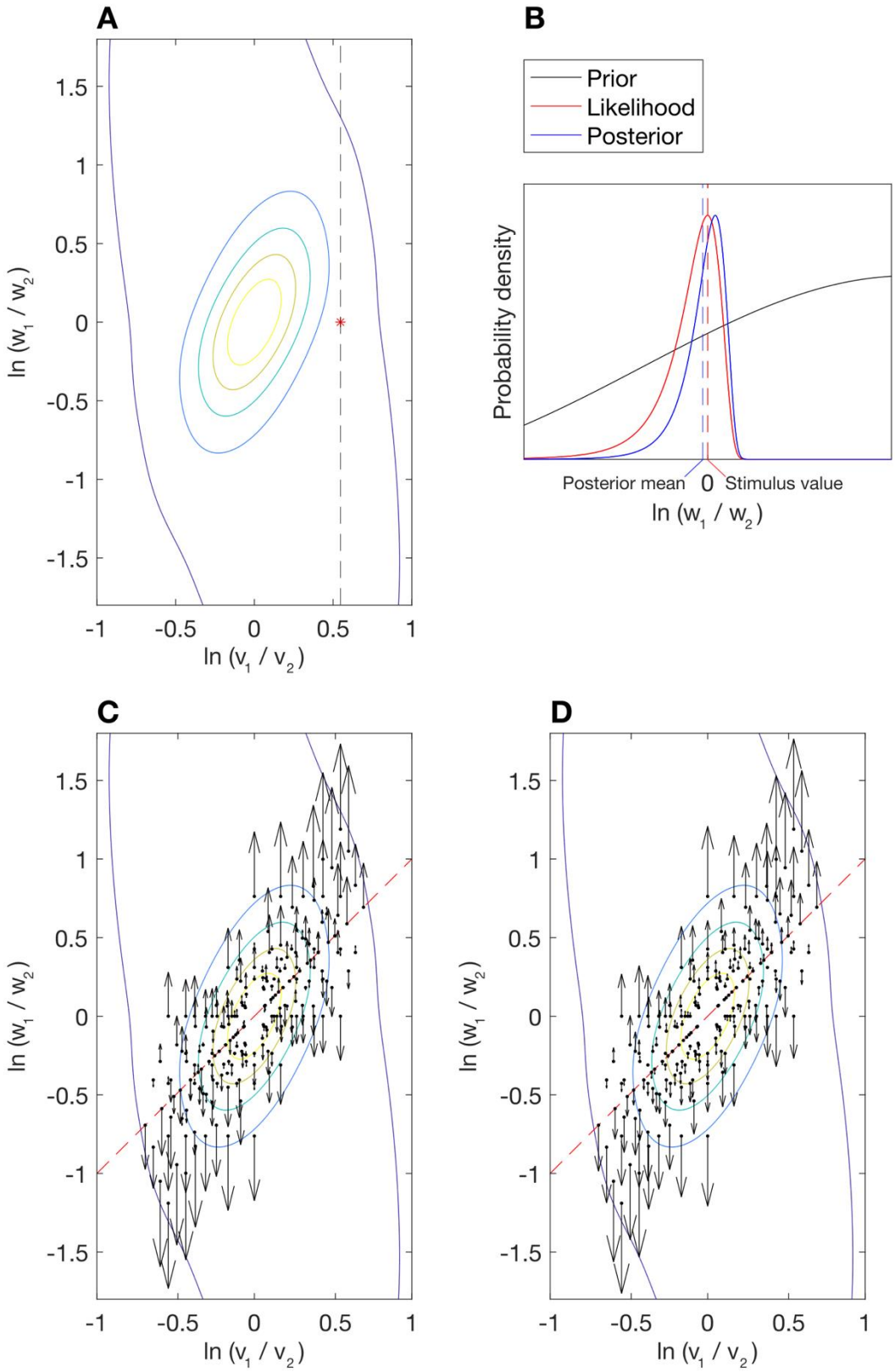
We present a simple model that includes a prior over two objects' relative weights and densities: the two dimensions of log weight ratio and log volume ratio. Such a prior, if aligned with the log weight ratio = log volume ratio unity line, represents the assumption that the two

objects have equal density. Perceptual biases away from this prior would be consistent with the 'contrast' or 'repulsion' explanation of the SWI that has prevailed for decades (5,16). For pairs of objects, considering ratios of weight, volume and / or density (rather than their differences) is a natural choice: any two of these ratios define the third, as $(w_1/w_2) / (v_1/v_2) = d_1/d_2$. Taking the log ratio gives a useful symmetry: $\log(w_1/w_2) = -\log(w_2/w_1)$; allowing us to predict the same magnitude of bias, irrespective of which object in a pair is designated as object 1. Our prior is defined by a mixture of three bi-variate Gaussians centred on [0, 0], i.e. equal weight and volume (Figure 6A). This mixture-model allowed us to explore variations in the shape of the prior; there is no reason to assume that it should be a perfect bivariate Gaussian. Model parameters and model comparisons given priors of different complexity are provided in SI, Table S3.

Similarly to Bays (29), we employ the simplifying assumption that perceptual estimates of volume ratio are relatively precise, and thus not significantly affected by the prior. Indeed, there is no clear evidence that objects with unexpected weights (e.g. typical SWI objects) cause biases in *volume* perception (i.e., a 'weight-size illusion' (53,54)). Thus, we estimated the expected bias in perceived log weight ratio by taking a slice through the prior at the true value of log volume ratio, and finding the slope of this 1D prior with respect to log weight ratio (Figure 6B). If volume ratio judgements were also available, one could drop the simplifying assumption, and simultaneously fit biases in log weight ratio and log volume ratio. The resultant fitted prior would have a slightly different shape.

We fitted the model via gradient descent to optimally predict biases in perceived log weight ratio, averaged across participants, for all unique stimulus pairs (N = 105). (For this model, we calculated each participant's ratio of weight estimates on each trial). Figure 6 shows the empirical biases in perceived log weight ratio (C) and those predicted by the model (D). The model accounts for perceived log weight ratio well, with 12 parameters (R^2 = .988; see SI S2. Efficient-coding Bayesian ratio model; Table S3). However, goodness-of-fit is poorer than our

descriptive model (Equation 1, 7 parameters), when parameters are optimised to minimise the SSR in perceived log weight ratio (R^2 = .991, see also cross-validation errors, SI Table S1). Nonetheless, this efficient-coding Bayesian model provides a theoretically appealing account of the SWI; biases in perceived log weight ratio are minimal around the d_1=d_2 identity line (dashed red lines in Figure 6 C-D) and increase with log density ratio, in line with repulsion away from an equal-density prior. Indeed, biases in log weight ratio correlate quite strongly with log density ratio (R^2 = .691).



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415 Figure 6 (A-B). Likelihood repulsion predicted by Wei and Stocker (30). (A) Bi-variate prior over
416 log weight and log volume ratio, optimised to minimise errors in predicted log weight ratio. (B)
417 The 1-D prior slice (solid black line) through the prior at the true log volume ratio (dashed line in
418 A), and a schematic of a median (unbiased / noise-free) observer likelihood and posterior for an

example stimulus pair (red asterisk in A). Efficient coding of stimulus properties results in skewed likelihoods (solid red line) with a long tail away from the peak of the prior. The posterior is also skewed (solid blue line). When a symmetric loss function is chosen, e.g. the mean (L2, blue dashed line) of the posterior, a bias away from the prior is predicted, i.e. the posterior estimate is shifted away from the prior peak, relative to the peak of the likelihood. (Nonetheless, this loss function minimises expected mean squared error). Measurement noise (expected to be skewed in stimulus space) further increases the predicted repulsive bias (30). (C-D) Biases in perceived log weight ratio. Contour lines show the prior; black dots show the stimulus pairs; arrows show the magnitude and direction of the bias for each pair; the red dashed line shows equal density. (C) Empirical biases; (D) predicted biases.

Tempting as it is to break out the champagne and toast our Bayesian brains, this may be premature. Closer inspection yields some difficulties with this model. First, the model is agnostic regarding how the bias in log weight ratio is split across the two objects. A reasonable assumption is that the prior has equal and opposite effects on the perceived weights of the two objects. However, this is not observed: there is only a weak correlation (R^2 = .283) between biases in estimates of log weight ratio and biases in estimates of log w_1 and log w_2 (log $\hat{w}_1$ – log w_1, log $\hat{w}_2$ – log w_2); biases in estimates of log w_1 and log w_2 are largely independent of the two objects' relative densities (R^2 = .215). Whilst biases in log weight ratio are *correlated* with log density ratio, the pattern of bias is fairly well approximated by a model that predicts each object's perceived weight from its weight and density, that is, independently of any interaction between the two objects (R^2, log weight ratio = .984; R^2, biases in log weight ratio =. 847 see SI, Table S1). This suggests that, although empirical biases are consistent with repulsion from an equal-density prior (Figure 6B), this might not be the underlying mechanism. Observed and predicted biases in judgements of log w_1 and log w_2 are shown in supplementary Figure S1.

Second, the model gives predictions for both biases and reliability (discrimination thresholds or estimate variability). According to the efficient coding model, more frequently observed stimuli are represented more precisely, such that discrimination thresholds are proportional to the reciprocal of the prior. At the individual observer level, our data provide poor estimates of discrimination (only two estimates per pair). However, at the group level, a systematic pattern is clear (see SI, Figure S2). Response variance is significantly correlated with

the log weight ratio (R^2 = .532); observers' judgements of relative weight are more reliable when the two objects' weights are similar. The Bayesian model provides a poorer account of response variance (model vs empirical: R^2 = .444, see SI, Figure S2). Indeed, as captured by our descriptive model, the effect of density on perceived weight is the largest when the weights of the two objects are similar (see Figure 4), that is, when the response variance is the smallest (see SI, Figure S2A). This is at odds with the efficient coding Bayesian prediction, in which more reliable judgements are associated with the least bias (see SI, Figure S2B). Unfortunately, therefore, this Bayesian model is not consistent with the behavioural data.

Finally, we also considered Bayesian models of perceptual bias involving a 2D prior over *differences* in weight and *differences* in volume or density (i.e. $w_1 - w_2$, $v_1 - v_2$, $d_1 - d_2$). A prior / model defined with regards to weight and volume differences is problematic: knowing the weight difference and volume difference of a stimulus pair leaves the density difference undetermined. This model thus (nonsensically) gives identical predictions of bias for a given weight difference, with either positive or negative density differences. In principle, a prior over weight and density difference is more plausible, given that our descriptive model predicts perceived weight difference as a function of weight difference and density difference. In practice, however, this model provides a worse fit to the observed biases in perceived weight difference (mixture of 2 Gaussian priors, 8 parameters; R^2 = .7690, SSR = 87140) than our descriptive model (which reduces to 4 parameters when predicting perceived weight differences, see Equation 2; R^2 = .9117, SSR = 1025.1). Moreover, the model predicts a completely different pattern of variance in estimated weight difference than the one observed (R^2 = .0017, p = .55).

4.3 Other models

We also fitted existing models by Bays (29), Peters and colleagues (28), and Wolf and colleagues (9) (see Introduction) to our data.

Bays (29) proposed a Bayesian model of the SWI, which, as above, predicts biases away from the prior, given efficient coding and an L2 loss function (30). However, rather than considering object pairs, Bays' model employs a bivariate Gaussian prior over the perceived weight and volume of single objects, i.e., a positive association between weight and size. Supplementary Figure S3 shows the model's fit to our data. We extended the model to incorporate a mixture of Gaussians prior (see SI, Table S4 for model parameters and model comparisons). Whilst the model captures the mean bias for each stimulus reasonably well, it cannot capture the way in which perceived weight is modulated by the other object in the pair, nor is it consistent with the pattern of response variance (see SI Figure S2).

We fitted Peters and colleagues' (28) model to our data. As described in the Introduction, Peters and colleagues assume a prior over weight and density ratio that is comprised of three sub-priors, representing three different classes of weight-density relationships (here re-expressed as weight-volume relationships, see Figure 1C). Figure 7 shows the empirical biases in perceived log weight ratio (A) and the predicted biases from the best-fitting model parameters (B). Sub-priors (represented by dashed lines) are encoded as bivariate Gaussians (See SI, Table S5 for model parameters and model comparisons). Unfortunately, the model cannot account for the set of biases in perceived log weight ratio across all stimulus pairs (R^2 = 0.413). It predicts a negative influence of log density ratio for some stimulus pairs; the predicted effect depends on where the stimuli lie relative to the three sub-priors. For example, in pairs of equal-volume (different weight, density) stimuli, log weight ratio is predicted to be underestimated as log density ratio, log weight ratio increase, whereas empirically it is overestimated.

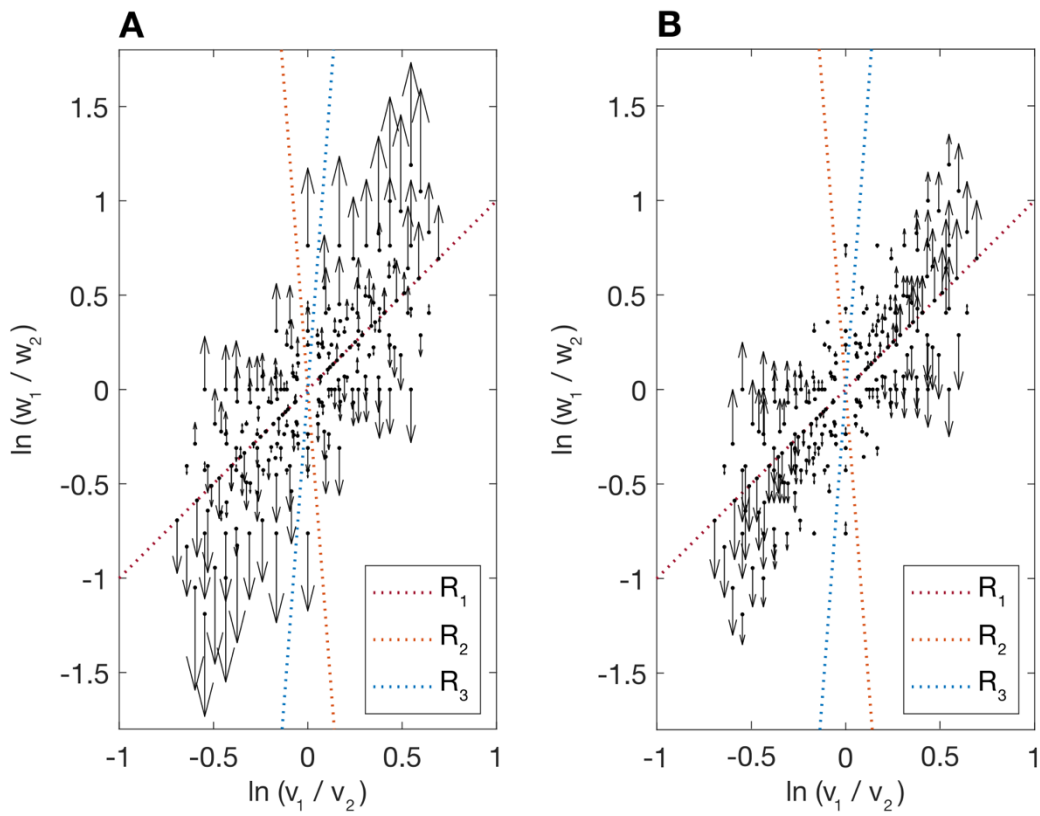

Figure 7 Biases in perceived log weight ratio. Dotted lines show the optimal three sub-priors from Peters and colleagues' model when fitted to our data. Black dots show the stimulus pairs; arrows show the magnitude and direction of the bias. (A) empirical biases; (B) predicted biases according to Peters and colleagues' model.

Finally, we evaluated Wolf and colleagues' (9) model with our data. In this model, perceived weight is a weighted average of weight and density estimates, weighted according to their relative reliabilities. Estimates are modelled as power functions of the corresponding physical feature. As we didn't manipulate the reliability of size information, the model reduces to:

$$\hat{w} = \beta_1 w^x + \beta_2 d^y \quad (4)$$

The model provides a reasonable account of perceived weight (R^2 = .96), although, like Bays' (29), it does not capture the contextual effects of the other object. Figure S5 (SI), shows

Wolf and colleagues' (2018) model fit to our data, for comparison with Figure 3; for model parameters and model comparisons see SI Table S6). Wolf and colleagues (9) suggest that the influence of density on heaviness perception depends solely on the reliability of size information used to infer density. In our experiment, therefore, with full access to visual and haptic cues, the contribution of density should have been constant. However, the influence of density was strongly modulated by weight difference (as shown in Figure 4A). As presented, our model does not encapsulate the additional effect of varying the reliability of size estimation; this would be accommodated by modulating the coefficients associated with density to reflect the availability of visual-haptic size cues (β_2, β_4, β_5, Equation 1). Lastly, Wolf and colleagues' model perceived weight and density as power functions of their physical counterparts. However, additional exponent parameters for weight or density were not statistically supported by our data. Wolf and colleagues had a 5:1 ratio of heaviest to lightest stimuli, compared to our reduced 3.3:1 ratio. It is likely that, given an increased range of stimulus weights / densities, our descriptive model would need to similarly include power functions of weight and / or density, in tandem with setting our intercept to 0.

5. Discussion

We investigated perceived heaviness in a set of stimuli which varied in weight and / or volume, and / or density in small steps. We report several novel findings: 1) The SWI occurs even at very small density (size) differences; 2) Across all stimuli, an object's weight and density are confounded / integrated to estimate weight; 3) Perceived weight is affected by the weight of the other object in a pair, but is largely invariant to the other object's density. 4) However, the influences of both objects' densities on perceived weight are strongly modulated by weight difference, with a negative, or 'contrast' effect of the other object's density appearing for similar weight pairs.

Our descriptive model captures the above effects, providing an excellent account of perceived heaviness (R^2 = .98) that captures the SWI as well as biases in perceived weight across a range of variations in pairings of stimulus weight and density. Additionally, we evaluated a novel efficient-coding Bayesian model of perceived weight ratios, alongside previously proposed models of the SWI. Here we will discuss our findings within the existing literature.

The magnitude of the SWI increased, as expected, with increasing density (size) difference (28,34,38,40). We extended this, by measuring the SWI with smaller density differences than those previously tested. We hypothesised that under small conflicts, the SWI might reverse (i.e., to show integration: smaller stimuli would be perceived as lighter). However, the SWI was clearly present for all equal-weight pairs, at odds with the idea that the SWI is driven by a (substantial) conflict between expected and perceived weight.

Our results are inconsistent with Peters and colleagues' (28)Bayesian mixture model. Also, at a conceptual level, the subdivision of the continuous world of size and volume/density into three relatively narrow categories is difficult to reconcile with environmental statistics. The best fitting parameters for our data assigns a prior probability of near 0 to equal-density objects (R_1, see Figure 7, and SI, Table S5). The other two sub-priors encapsulate the expectation that smaller objects are either much heavier and denser (R_2) or much lighter and less dense than larger ones (R_3), both at odds with reported natural statistics for everyday liftable objects (27).

The efficient-coding Bayesian ratio model provides a theoretically appealing account of the SWI, predicting a repulsion away from a plausible equal-density prior. However, neither our efficient-coding Bayesian ratio model, nor that recently proposed by Bays (29) satisfactorily account for our pattern of data. Whilst our efficient-coding model provides a reasonable fit to the empirical biases in perceived log weight ratio, the inferred biases in perceived log w_1 and log w_2 do not match those observed (which are largely invariant to the ratio of the two densities). In addition, as highlighted by the descriptive model, the perceived weight of an object is *only*

influenced by the other object's density when the two weights are similar, i.e. when discrimination thresholds are smallest. In contrast, the efficient-coding Bayesian model predicts that biases will be smallest when discrimination is best (see SI, Figure S2).

As noted above, neither Bays' model (29) nor Wolf and colleagues' model (9) account for contextual bias effects found in our data (influence of w_2 and, in certain conditions, d_2), and neither is Bays' model consistent with empirical patterns of response variance.

So, is the SWI Bayesian after all? We don't think so; the SWI does not appear to be caused by repulsion from an equal-density prior. It is reasonable to assume that the perceptual system does expect same-material objects to be same-density. Indeed, the sensorimotor system may rely on an object's size, together with density expectations for classes of objects / materials to infer the weight of a stimulus prior to lifting (12). Such expectations presumably drive the initial (erroneous) forces used when lifting SWI objects (55). However, the illusion persists after forces quickly adapt to the true weights, and the SWI is just as large when same-density cues are reduced, i.e., when the colour or surface material of the two stimuli differs (56,57).

In general, perceived weight was modulated by density; denser objects are perceived as heavier than less dense objects, consistent with previous literature (9). In line with Wolf and colleagues (8,9) weight does appear to be routinely confounded / integrated with density information. However, our data reveal that the effect of density is substantially increased when equal-weight objects are encountered, as in the typical size-weight illusion. Thus, like Bays' (29) model, Wolf and colleagues' (9) model fails to capture the contextual effects of the other object. Rather, these models predict biases in perceived weight that occur in single-object judgements (see, e.g., (58)). Obviously, object perception occurs in various contexts, not only object pairs. Our model could be generalised to judgements of single objects, by replacing the other object's properties with a weighted combination of previously encountered stimuli.

6. Conclusions

Our study situates the SWI in the broader context of weight perception under varied conditions (combinations of volume, weight, and density) allowing us to evaluate different models of weight perception, including our own model.

Our explorations reveal that, whilst the SWI magnitude increases with size / density difference, it occurs even for small density differences. Second, we showed that typical SWI experiments have inflated estimates of the influence of density on weight perception more generally. The effect of density on perceived weight is substantially smaller when two objects of different weights are encountered. Our simple model provides an excellent *descriptive* account of perceived weight under various combinations of size, weight, and density. Our model, however, is not explanatory: We still don't know why the SWI occurs. Why do we conflate weight and density, and why is this effect magnified when weight differences are small?

We explored different avenues to reconcile the SWI within the Bayesian framework, given the appeal of finding a model that could provide an explanatory account of weight perception in the SWI and beyond. However, none of the Bayesian models we tested, including efficient-coding models that do predict biases away from a prior, could successfully account for our data.

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