Perceptual Load and Enumeration: Distractor Interference Depends on Subitizing Capacity

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Abstract

Attention is limited, both in processing capacity (leading to phenomena of 'inattentional blindness') and in the capacity for selective focus (leading to distraction). Load Theory (e.g. Lavie, 1995) accounts for both limitations by proposing that perceptual processing has limited capacity but proceeds automatically and in parallel on all stimuli within capacity. Here we tested these claims by applying Load Theory to the phenomenon of 'subitizing': the parallel detection and individuation of a limited number of items, established in enumeration research. We predicted that distractor interference will be found within but not beyond a person's subitizing capacity (measured as the transition from parallel to serial slope). Participants reported the number of target shapes from brief displays while ignoring irrelevant cartoon-image distractors. As predicted, distractor cost on enumeration performance was found within subitizing capacity and eliminated in larger set sizes. Moreover, individual differences results demonstrated that distractor effects depended on an individual's capacity (i.e. their serial-to-parallel transition point), rather than on set size per se. These results provide new evidence for the Load Theory hypotheses that perceptual processing is automatic and parallel within its limited capacity, while extending it to account for selective attention during enumeration.

Keywords: Attention, Perceptual load, Subitizing capacity, distractor interference, individual differences

Public Significance Statement

Why is it that people are sometimes distracted by information that is irrelevant to their task, while at other times can experience inattentional blindness to anything outside their attention focus? Here we relate attention theory to the phenomenon of subitizing- the instant detection of a small number of stimuli- typically up to five. We establish that whether a person perceives a distractor, or is inattentionally blind to it, is determined by the task demands on their perceptual capacity. In task of low attention demands ‘spare’ capacity results in perception of a task-irrelevant stimulus and this can result in distraction, otherwise if task demands take up full perceptual capacity, this results in reduced ‘distractor’ perception outside attention focus. Moreover, we show that individuals differ in capacity: people with a higher perceptual capacity (who can instantly subitize more items) perceive items outside their focus in tasks that exhaust capacity for lower-capacity individuals.

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Visual perception is capacity-limited, and this can be painfully evident when one fails to notice important information outside their focus of attention, for example information critical for driving safety, such as a vehicle approaching. Much research has now established a variety of such 'inattentional blindness' phenomena when perceptual capacity is loaded (e.g. Cartwright-Finch & Lavie, 2007; Simons & Chabris, 1999). However other lines of research have demonstrated that people may often find it impossible to ignore irrelevant distractors, even when failing to ignore them causes interference to performance of the attended task at hand (e.g. Eriksen & Eriksen, 1974; Lavie, 1995; Theeuwes, 1991; see Lavie, 2005; 2010; Lavie & Tsal, 1994 for reviews). The opposing ways in which attention can fail have been explained by the Load Theory of attention: Load Theory (e.g. Lavie,1995) proposes that perceptual processing has limited capacity but proceeds in parallel on all stimuli within capacity limits in an automatic and involuntary manner. Cognitive control is restricted to setting processing priorities (e.g. higher processing weight for task-relevant over task irrelevant processing), however if task-relevant processing does not take up full capacity, spare resources are allocated in parallel, involuntary manner to the low priority (task-irrelevant) stimuli. Thus, only in task conditions of high perceptual load, which exhaust capacity in task-relevant processing, will irrelevant distractors fail to be perceived. However, in task conditions of low perceptual load that leave spare capacity, irrelevant distractors will be perceived and can produce distractor interference effects

As we briefly review below, much support for these claims has been derived from studies demonstrating that distractor processing critically depends upon the level of perceptual load in the attended task. These studies have used various manipulations of perceptual load and different indices of distractor processing (see Lavie, 2005; Lavie et al. 2014; Murphy et al. 2016 for reviews). The results provide evidence that while people experience inattentional blindness to task-irrelevant stimuli in conditions of high perceptual load they fail to ignore distractors in conditions of low perceptual load. This research clearly established the critical role of perceptual load in distractor processing. The Load Theory claim that perceptual processing proceeds in parallel on all stimuli within capacity has so far received support from a smaller body of studies demonstrating continued distractor processing in cases of only moderate increases in perceptual load that are likely to remain within the available capacity (Forster & Lavie, 2008a; Lavie & Cox, 1997; Lavie & Fox, 2000). Given the importance of this claim to the understanding of the nature of perceptual processing we sought in the present study to directly test this hypothesis by relating it to the phenomenon of subitizing: the parallel detection and individuation of a small number of stimuli as established in enumeration research. Subitizing capacity is defined as the number of items that can be detected and individuated in parallel (both processes are critical in order to report the number of items from a brief display commonly measured in Enumeration research). In contrast, enumerating larger numbers that are beyond subitizing capacity is known to depend on the display set size, with RTs increasing in a serial fashion. Thus, the point of change in the slope of the RT or error rate x set size function in enumeration performance from parallel to serial slope can provide us with a clear criterion for the limits on a person's capacity Moreover, subitizing has recently been shown to provide a robust predictive measure of perceptual capacity across diverse tasks (Eayrs & Lavie, 2018; 2019). Therefore, subitizing capacity can be used to establish the levels of perceptual load that can be accommodated within a person's capacity. We thus propose that by measuring distractor processing during enumeration and relating this to subitizing capacity (based on the clear criterion of the breakpoint in the slope of the RT or error rate set size function) we can provide a novel test of Load Theory prediction of parallel automatic processing that leads to distractor interference within but not beyond perceptual capacity.

Evidence for the Role of Perceptual Load in Distractor Processing

Much support for Load Theory has accumulated over years of research using numerous experimental paradigms and both behavioural and neuroimaging measures. For example, perceptual load in visual search tasks has been manipulated by increasing the search set size or the similarity between a target and non-targets: an angular target letter might be presented among homogeneous circular letters (low perceptual load) or among other heterogeneous angular letters (high load). Distractor effects were measured from an irrelevant distractor letter or object presented in the periphery using various measures of distractor interference such as response competition (e.g. Lavie & Cox, 1997; Lavie & Fox, 2000; Roper et al., 2013), negative priming, repetition priming (Lavie et al., 2009; Lavie & Fox, 2000) and RT costs produced by the presence (vs. absence) of entirely irrelevant distractor objects (Forster & Lavie, 2008a; 2008b). Distractor effects so measured were found in conditions of low load and were consistently reduced when the task involved higher perceptual load. Many studies have generalised the effects of perceptual load across manipulations that vary the perceptual processing requirements for the same visual stimuli. For example, the perceptual demands of a task involving just one stimulus at fixation have been varied by requesting participants to either detect a simple feature (e.g. colour – low load), or discriminate between conjunctions of features (e.g. colour and orientation, high load; Carmel et al. 2011; Molloy et al. 2019) in tasks using the 'rapid serial visual presentation' paradigm. Perceptual load has similarly been manipulated for just one stimulus at fixation in 'inattentional blindness' tasks, comparing simple detection (either of colour or of line length for crosshair lines that are very different in length) in the low load conditions, or more fine-grained discrimination (of small differences in line-length) in high load.

Studies assessing the impact of perceptual load on detection sensitivity, orientation tuning, and the contrast response function have further reinforced that these effects reflect reduced perceptual processing outside the focus of attention (e.g. Lavie et al. 2014; Macdonald & Lavie, 2008; Raveh & Lavie, 2015; Stolte et al, 2014). Neuroimaging research has also demonstrated reduced neural response to the distractors in visual cortex (Rees et al., 1997; Schwartz et al., 2005) and auditory cortex (Handy et al., 2001 Molloy et al. 2015; Molloy et al. 2019) under conditions of high perceptual load in the task.

Previous Tests of the Load Theory Hypothesis of Parallel Processing Within Perceptual Capacity

The majority of research so far has compared perceptual load effects between two levels: low versus high load. In all the paradigms used in the research described above, the conditions of low load were designed to be within the perceptual capacity limits of any individual, while the conditions of high load were designed to exceed the capacity of all individuals. A smaller body of research, using the visual search paradigm to measure the processing of irrelevant distractors during search, has manipulated gradual increases in perceptual load to examine the Load Theory hypothesis of parallel and automatic processing within capacity. This hypothesis predicts that an irrelevant distractor, presented outside of the search array, will nevertheless be involuntarily perceived as long as the number of items involved in the search task (i.e. the search set size) does not exceed perceptual capacity. Lavie and Cox, (1997) asked participants to search for one of two target letters among a varying number of 'non-target' letters arranged in a circle around fixation, and to respond by indicating the target identity (e.g. press one key for the letter 'X' or another for the letter 'N'). Participants were also instructed to ignore an irrelevant distractor appearing in the periphery, which could be either congruent, incongruent or neutral with respect to the target letter. Distractor processing was measured by means of response competition effects produced by the congruent versus incongruent (or neutral) distractor conditions. The distractor effects were found to be unaffected by gradual increases in search set size thought to be within capacity within the specific search task (e.g. typically up to four items in studies using the letter search task originally devised by Lavie and Cox, 1997) and were only eliminated with larger set size increases. This pattern of findings was replicated (e.g. Remington et al., 2012; Roper et al., 2013) and generalised also across other types of distractors and different versions of visual search tasks (e.g. involving search for a target name or for a face while ignoring meaningful distractor objects and faces – Lavie et al. 2003; Thoma & Lavie, 2013). The same pattern of results generalised also across different measures of distractor processing during search including negative priming, and RT cost produced by the presence (vs. absence) of an entirely irrelevant distractor (Lavie & Fox, 2000; Forster & Lavie, 2008a). Although all these studies have included varying levels of perceptual load, they did not attempt to identify the precise level of set size that exhausts capacity. Instead they have typically compared distractor processing in small set sizes up to three or four items (that were considered within-capacity set sizes) and set sizes of six or larger considered to be beyond-capacity (Note 1). The convergence of findings across different experiments and measures upon the same conclusion, namely that an irrelevant distractor is processed only in search set sizes of up to four items, provides support for Load Theory's proposal of parallel, automatic processing of all items within capacity. However, given that all of these studies used the visual search paradigm it remains desirable to examine this claim in a different paradigm, and in particular one that allows for a formal definition of perceptual capacity limit based on determining the number of items that can be processed in parallel

Here we therefore examined the Load Theory hypothesis that perception of all items (including task-irrelevant distractors) is parallel and automatic within capacity, by relating perceptual load to the phenomenon of 'subitizing' which has also been taken to reflect a process of parallel detection and individuation of a small number of items (typically up to four). As we briefly discuss below, the application of Load Theory to the subitizing paradigm also allowed us to clearly identify when a particular level of perceptual load exhausts capacity based on parallel versus serial set size slopes in enumeration. This in turn allowed us to test an important prediction concerning individual differences in perceptual capacity, specifically whether the point at which an individual's perceptual capacity is exhausted serves as the threshold for the effect of set size on distractor processing, specifically whether increased set size in the display only affects distractor processing when the increase leads to surpassing the limited capacity threshold for processing items in parallel.

Subitizing and Perceptual Capacity

Although the phenomenon of subitizing has been traditionally established in visual enumeration research it appears to mirror the Load Theory proposal of capacity-limited perception that involves parallel processing within capacity. When presented with a variable number of stimuli and asked to report the quantity, participants are typically able to report a small number of items (typically up to around four items) rapidly and accurately, and their performance measure (i.e. RT or accuracy) by set size function shows a parallel slope within their 'subitizing range'. For larger sets, a serial performance by set size function is observed, whereby reaction times and error rates increase monotonically with each additional item. This is true for simple shapes and complex real-world stimuli (Railo et al., 2016) and for brief or long stimulus presentations (Mandler & Shebo, 1982).

Thus the Load Theory hypothesis that all items that are within a person's capacity should be perceived in a parallel, automatic manner (including irrelevant distractors as well), appears to be in common with the underlying notion of subitizing as reflecting a parallel automatic process with a limited capacity. We thus propose that the same limited capacity attention mechanism suggested by Load Theory also underlies the phenomenon of capacity-limited subitizing.

In line with this, recent research has demonstrated that individual differences in subitizing capacity significantly correlate with individual differences in perceptual capacity. This includes the typical visual attention paradigms of "change blindness" (involving flickering complex scene images), load-induced inattentional blindness, and multiple object tracking capacity (MOT), which along with subitizing, form a distinct factor dissociable from cognitive control functions (Eayrs & Lavie, 2018). Indeed, previous research has shown that subitizing capacity is reduced in a one-to-one fashion for stimuli presented during performance of a multiple object tracking (MOT) task (Chesney & Haladjian, 2011) such that for each additional item that a participant was required to track in an MOT task, their capacity to subitize was reduced by one. These findings are strongly suggestive of a shared underlying resource.

Neuroimaging research has suggested that this shared resource depends on grey matter volume in posterior parietal cortex (PPC). Eayrs and Lavie (2019) have recently demonstrated that individual differences in PPC grey matter volume are predictive of the common perceptual capacity factor underlying variance in performance of subitizing, change blindness and MOT. Furthermore, this correlate was specific to perceptual capacity and distinct from correlates of the capacity for cognitive ‘executive’ control (which were found in left frontal cortex). Indeed, prior functional and structural imaging research has demonstrated that subitizing is associated with activity in parietal regions associated with visual awareness (Cutini et al., 2014; Vetter et al., 2011) and that these correlates are distinct from other forms of numerical processing, such as exact counting (Ansari et al., 2007). If subitizing capacity indeed reflects perceptual capacity, then Load Theory leads to specific predictions for irrelevant distractor processing during visual enumeration: Since perceptual processing proceeds in parallel within capacity to include also irrelevant distractors, then distractors should be perceived across all set size levels within subitizing capacity, but not in set size levels that exceed capacity. Thus distractor processing should be unaffected by the increase in set size, as long as the set size increase does not surpass perceptual capacity limits. Moreover, the impact of set size on distractor processing should be related to individual differences in subitizing capacity. Distractor processing should be reduced at higher set sizes for individuals with larger subitizing capacity, compared to those with lower capacity for whom a smaller set would already exhaust their more limited capacity.

We tested these predictions in the present study by presenting an irrelevant distractor while participants performed an enumeration task. Participants were required to enumerate items presented within a circular display and instructed to ignore a task irrelevant distractor (a cartoon image, see (Forster & Lavie, 2008b) presented infrequently at fixation. Distractor processing was measured as the cost to the enumeration task performance accuracy or RT in the presence versus absence of the distractor. Capacity limits were determined for each individual by identifying their bifurcation point from parallel to serial slope in the enumeration accuracy (Experiment 1) or RT (Experiment 2) set size functions.

Experiment 1

Method

Participants

An entire class of ~100 undergraduate psychology students was invited to participate. From this, a total of 84 students, took part in the experiment. Power analysis conducted using G*Power based on the effect sizes observed in (Forster & Lavie, 2016) a sample of n = 19 would be required for 85% power to detect the effects of high (vs. low) perceptual load on distractor interference costs ($\alpha = .05$, $dz = .74$). Our sample therefore provided more than adequate power to estimate a similar effect (although our manipulation of load was more fine-grained and therefore likely to require a larger sample). Participants were excluded from analysis if their response accuracy was below 60% correct on the lowest set size of the enumeration task (set size one) on trials where no distractor was present. This resulted in the exclusion of six participants, and the final sample analysed was therefore n = 78 participants (63 female), aged 18-23 (M = 19.14, SD = 1.26). All participants reported normal or corrected to normal vision.

Stimuli and Procedure

The experiment was prepared and presented in Matlab (Mathworks, Inc., Natick, MA) using the Cogent toolbox (www.vislab.ucl.ac.uk/cogent.php) on a PC with a 15-inch flat screen monitor. Participants were seated individually in a testing cubicle. Attached to the bottom of each monitor was a 60 cm length of string, which participants were instructed to use to establish a 60 cm distance from their chin to the monitor. They were asked to maintain this distance for the duration of the experiment, but head position was not constrained.

Figure 1 (top panel) presents an example of the stimuli presented on each trial. Each stimulus display consisted of 11, 12 or 13 Gabor patches, each subtending 2.4° of visual angle. The patches were arranged in a ring, 9° in diameter around the centre of the screen. A variable number of one to nine enumeration target patches was presented on each trial. Non-target patches were vertically oriented with a contrast of 50% and targets were of horizontal orientation and a 100% contrast. The total number of (target and non-target) stimuli per display (11-13) was varied randomly to ensure that the number of non-targets could not be used to determine the number of targets in higher set sizes (i.e. by subtracting the smaller number of non-targets from a known total).

On one third of trials an irrelevant distractor was presented in the centre of the screen. This consisted of an image of one of six cartoon characters (Mickey Mouse, Daffy Duck, Spongebob Squarepants, Pikachu, Spiderman, and Superman) and was presented within a black square. The square subtended 4.8° and the cartoon character was approximately 2.2° by 2.5° at the viewing distance of 60 cm. The mask which followed the stimulus display was made up of 48 black and white circles arranged randomly in a ring covering the same area as the enumeration stimuli (see Figure 1a).

On each trial, a central fixation cross appeared for 1,000 ms followed by a stimulus display for 200 ms. The stimulus display was followed immediately by a response screen with a visual mask for a further 5,000 ms or until the participant responded. On one third of trials a cartoon character image appeared in the centre of the screen simultaneously with the enumeration stimuli.

Participants were instructed to press a button from 1-9 on the number pad of the keyboard to indicate how many targets had been presented. They were told to be as accurate as possible and to ignore the cartoon images entirely. The target set size (1-9), the total number of stimuli (11-13) and distractor condition (present on one third of the trials and absent on the remaining two thirds) were counterbalanced such that each block included an equal number of trials with these combinations, this resulted in 81 trials per block. After one practice block of 10 trials, participants completed four experimental blocks with a self-paced break in-between blocks.

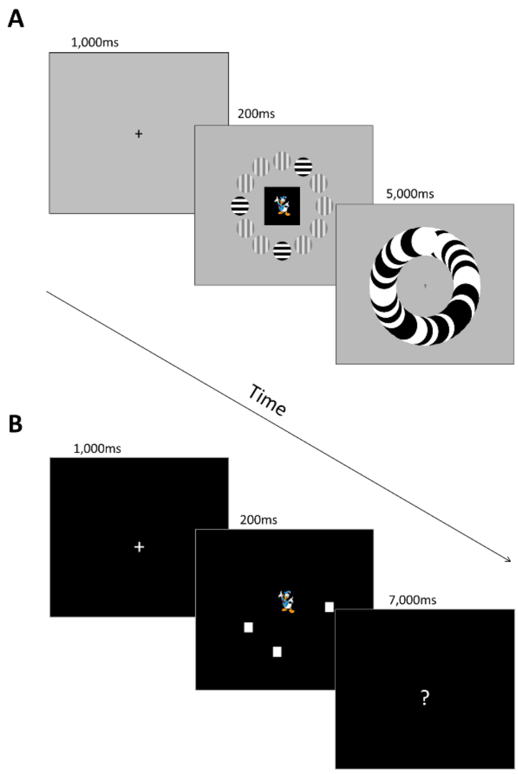

Figure 1. Trial examples in Experiments 1 (A) and 2 (B).

Results and Discussion

Figure 2 displays the average enumeration task error rates as a function of set size on distractor absent trials (top panel) and proportional distractor effects, at each set size up to set size eight (bottom panel). As can be seen in the figure, the slope of the error-rate x set size function was flat (indicating parallel processing) for set sizes one to two, then steepening (suggesting a serial pattern) from set three to four and became steeper beyond set size four, reaching asymptote at set size eight. This was confirmed in a one way ANOVA that indicated a main effect of set size on error rates, $F(7, 539) = 574.93$, $p < .001$, $\eta_p^2 = .88$. There was a significant linear trend, $F(1,77) = 2404.27$, $p < .001$, $\eta_p^2 = .97$, a significant quadratic trend, $F(1,77) = 27.15$, $p < .001$, $\eta_p^2 = .26$, and a significant cubic trend, F(1,77) =

191.32, $p < 001$, $\eta_p^2 = .71$. We note however that as these data represent error rates averaged across all participants, the pattern is most likely to reflect a declining number of people who were able to subitize sets of three or more items in parallel.

Distractor interference effects were calculated for each set size, up to set size eight (Note 2) as the percentage increase in error rates in the distractor present versus absent conditions, by subtracting error rates in the distractor-absent condition from error rates in the distractor-present condition and dividing the result by the distractor-absent error rate.

A within-subject ANOVA on the proportional distractor cost as a function of set size indicated a main effect of set size, $F(7,539) = 17.04$, $p < .001$, $\eta_p^2 = .18$. As can be seen in Figure 1 (bottom panel) this effect reflected reduced distractor effects with increased set size. Importantly, pairwise comparisons indicated significant distractor costs in set sizes one to four which have all passed the Bonferroni corrected alpha level of $p < .006$ for eight comparisons [set size one, $t(77) = 9.49$, $p < .001$, $d = 1.08$ BF_{10} 101962.90; set size two, $t(77) = 8.04$, $p < .001$, $d = 0.91$, $BF_{10} = 4481.04$; set size three, $t(77) = 6.05$, $p < .001$, $d = 0.69$, $BF_{10} = 322.79$, and set size four, $t(77) = 2.83$, $p = .006$, $d = 0.32$, $BF_{10} = 13.82$] while no significant distractor effects were found for the higher set sizes [Set size 5, $t(77) = 1.46$, $p = .15$, $d = 0.17$, $BF_{10} = 0.344$; set size 6, $t(77) = 1.57$, $p = .122$, $d = 0.18$, $BF_{10} = 0.40$; set size 7, $t(77) = -1.15$, $p = .26$, $d = -0.13$, $BF_{10} = 0.23$; set size 8, $t(77) = 0.90$, $p = .37$, $d = 0.10$, $BF_{10} = 0.19$] in fact there was no effect above zero (as can be seen in Figure 2 bottom panel).

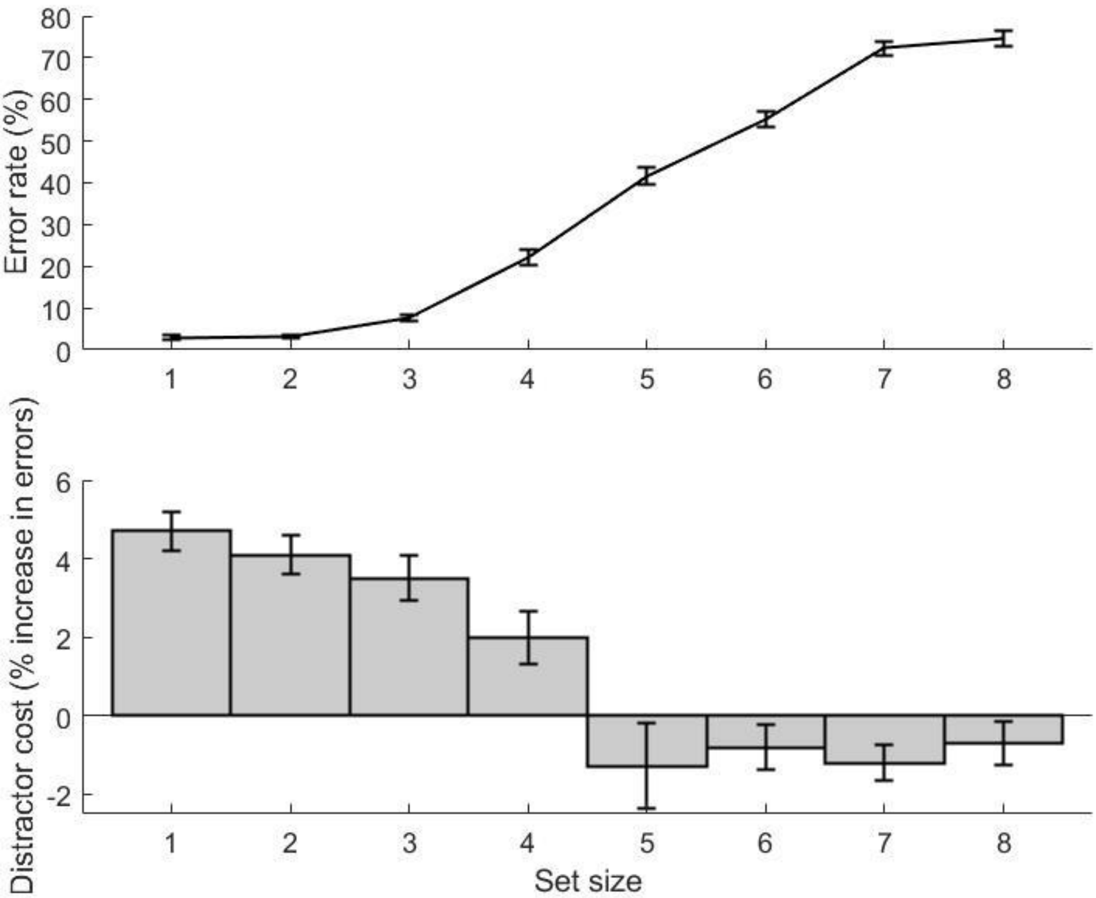

Figure 2. Top panel – percentage error rates as a function of set size, in the distractor absent conditions in Experiment 1. Bottom panel – percentage distractor costs calculated as the proportional increase in percentage errors in the distractor present condition (P) compared to the distractor absent condition (A), (i.e. P-A/A) plotted as a function of set size.

Individual Differences

While the group-level results demonstrated an interaction between set size and distractor costs, averaging across the sample smooths over any individual differences in capacity limits. Our main hypothesis was that distractor effects would only be affected by increased set size when the increase in set size leads to surpassing an individual's capacity limit. While set size increases concerning set sizes that are both within capacity, or both beyond capacity should not affect distractor processing. In other words, the capacity limit serves as the critical threshold for the effects of increased set size on distractor processing. Thus we predict a step change between distractor costs produced when processing of all items is within capacity and their elimination once the set size exceeds a person's limited capacity. To obtain the individual subitizing capacity limits on the basis finding the point of transition from parallel slope (within capacity) and serial slope (beyond capacity), we fit two functions to each participant's accuracy data, one bilinear and one sigmoidal. First, the bilinear function was fit to the individual error-rate data. The function consisted of two linear components, the first with a slope fixed at zero and the second with a positive slope. The function tested every possible intersection point in steps of 0.01 and every possible slope for the second linear component between 1 and 50 (% error) in 1-point steps.

This was contrasted with individual capacity estimate based upon a sigmoidal function fit to the same data using the 'ISRCalculator' function described by Leibovich-Raveh et al. (2018). This algorithm first fits a standard sigmoidal function to the individual participant's accuracy data, then takes the intersection point of two lines, the first being a flat line (zero slope) intersecting the y-axis at the same point as the sigmoid where x = 0, the second being the tangent of the sigmoid at its inflection point in order to identify the bifurcation point.

For the bilinear function the average adjusted R^2 was .91 (SD = .08), demonstrating a good fit to the data. The average fit of the sigmoid-based model was better (average R^2 =

.94, SD = 0.05). A sigmoid function fit was thus used to estimate individual subitizing capacity in this experiment. The average subitizing capacity across all individual estimates was 3.46 (SD = 0.83, Range: 1.54 – 5.78, see Figure 3), in line with capacity estimates of three to four items typically reported in previous research.

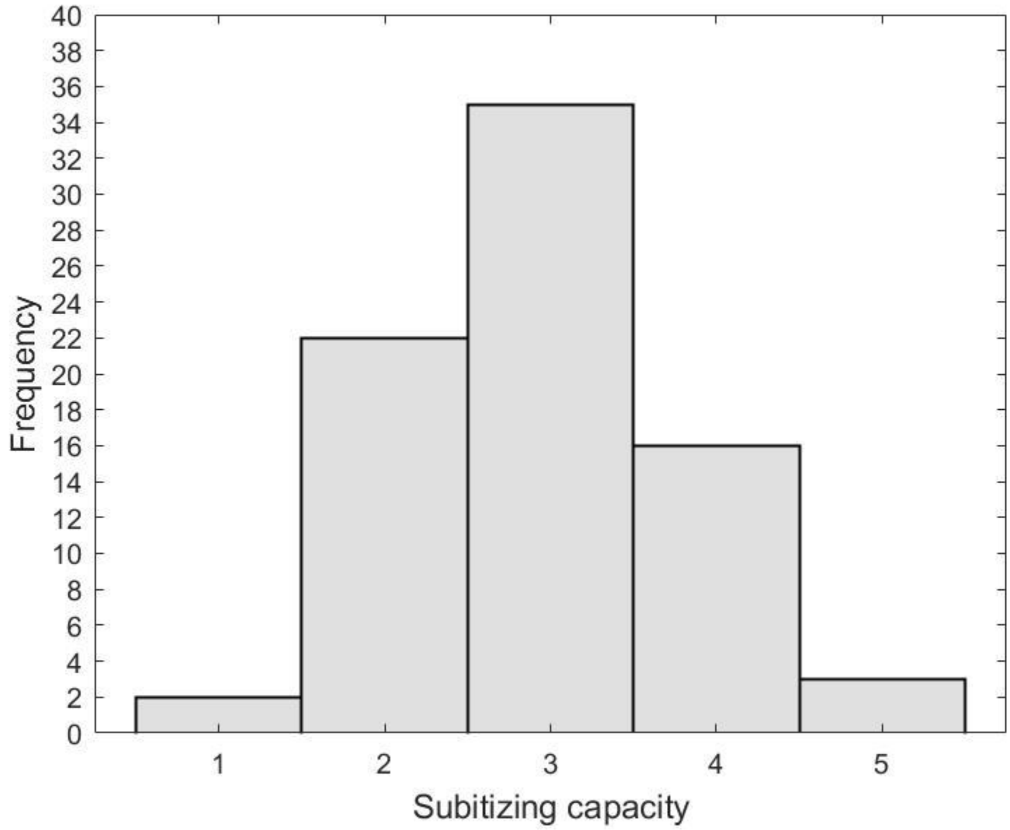

Figure 3. Histogram of subitizing capacity estimates derived using the sigmoidal fit and expressed as display set size, with capacity value binned to the lower set size integer (i.e. capacity estimates between ‘x’ and ‘x.9’ are binned within ‘x’ set size).

As a first test of the role of capacity in the effect of set size on distractor interference, we re-ran the ANOVA presented above, this time including subitizing capacity as a covariate. The interaction between subitizing capacity and the effect of set size was significant, $F(7, 532) = 2.04$, $p = .048$ $\eta_p^2 = 0.26$ suggesting a role for capacity in determining set size effects on distractor processing.

To further elucidate the role of individual differences in subitizing capacity, we calculated the distractor cost for each set size, specifically considering whether the effects are for set sizes within capacity or beyond capacity for each individual (as per their bifurcation point). Since the bifurcation point was expressed in non-integer values (e.g. 2.6), while set size was always an integer value, for any bifurcation value of x.0 to x.9 all set sizes up to and including x were considered as within capacity, and all those beyond x+1 were considered as clearly beyond capacity. Set size x+1 was considered a capacity borderline set size (since for an individual with a bifurcation value of say 3.7, set size 3 is clearly within capacity, and set size 5 is clearly beyond capacity while set size 4 lies at the border (since the 3.7 estimate suggests that in some of the set size 4 trials the accuracy did not show the sharp decline found beyond subitizing capacity). Importantly, because there were individual differences in capacity, as shown in Figure 3, this led us to considering different set sizes as either within or beyond capacity for different participants (Note 3). To provide additional support for the null effects and for the lack of distractor interference at supra-capacity set sizes, Bayes factors were calculated for each comparison to evaluate the strength of the evidence for or against the null hypothesis (of zero difference in distractor cost).

Figure 4 presents the distractor cost per each set size relative to individual capacity, and Table 1 presents the comparison against zero for distractor cost in each of these set sizes. As can be seen in Figure 4 distractor interference produces a clear accuracy cost in all set sizes within capacity while no distractor cost is found in set sizes clearly beyond capacity.

The results shown in Table 1 confirm these observations. Distractor costs for each within-capacity set size were all significant, and the Bayes factors all provided decisive evidence for H1. In contrast, distractor costs for set sizes beyond capacity were not significant and the Bayes factors provided substantial evidence for the null hypothesis (i.e. that distractor cost scores are no different from zero).

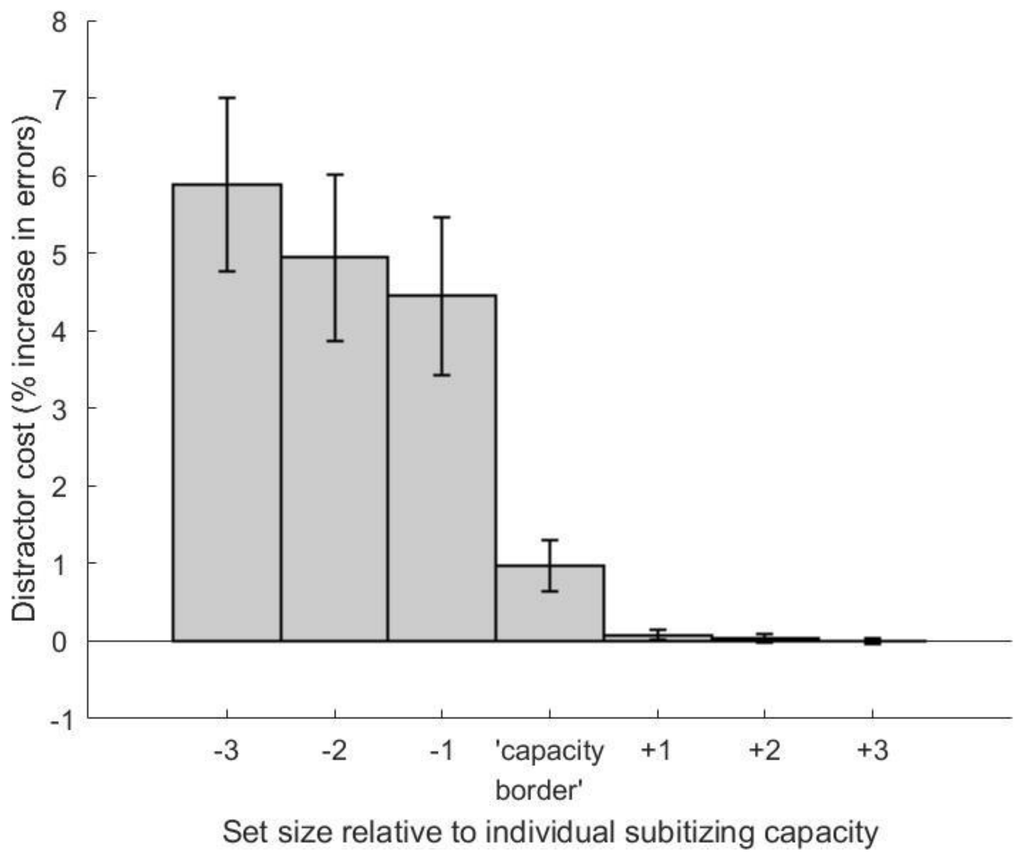

Figure 4. Bar graph of mean distractor cost as a function of set size increase or decrease relative to individual subitizing capacity estimates, error bars represent one SEM.

Table 1: Results of pairwise comparisons against zero for each capacity-relative set size in Experiment 1

Set size relative to individual capacity border	**Sample size**	**t-test against zero**	**Bayes factor against zero**
Border minus 3	54	t(53) = 5.26, p < .001, *d* = 0.72	BF_{10} = 6531.09
Border minus 2	76	t(75) = 4.64, p < .001, *d* = 0.53	BF_{10} = 1206.92
Border minus 1	78	t(77) = 4.37, p < .001, *d* = 0.50	BF_{10} = 484.50
Border	78	t(77) = 2.91, p = .01, *d* = 0.33	BF_{10} = 6.10
Border plus 1	78	t(77) = 1.23, p = .22, *d* = 0.14	BF_{10} = 0.25
Border plus 2	78	t(74) = 0.53, p = .60, *d* = 0.06	BF_{10} = 0.14
Border plus 3	75	t(74) = -0.21, p = .83, *d* = -0.02	BF_{10}= 0.13

Our hypothesis also predicts a significant difference in distractor costs between those found within capacity and those found beyond capacity. This was supported in a comparison of distractor costs between the top ‘within capacity’ set size (i.e. borderline set size minus one) and the first set size that is unambiguously 'beyond capacity' (i.e. borderline set size plus one) were significantly different, $t(77) = 4.26$, $p < .001$, $d = .48$, $BF_{10} = 337.81$.

In order to establish that this difference is attributable to the transition from within- to beyond-capacity rather than the mere increase in set size, we also compared the distractor costs in the 'borderline minus one' set size versus 'borderline minus three' set size. In this way we assess an equal increase in set size (two items difference) as that in our previous comparison (of borderline set size plus one with borderline set size minus one) but both are considered as within capacity set sizes. Importantly because both set sizes are within individual capacity limits the distractor cost were not expected to differ in this comparison, even though the increase in set size is exactly the same as in the previous comparison. As predicted, the difference in distractor cost score was not significant, $t(53) = 1.301$, $p = .20$, $d = 0.18$, $BF_{10} = 0.33$ providing substantial evidence for the null hypothesis. Similarly, we also compared distractor cost scores for two set sizes beyond capacity with a matched step-size (of an increase in two items) and once again, despite the matched increase in set size, we predicted no increase in distractor cost as both set sizes are beyond capacity and should therefore leave no capacity spare for distractor processing. As predicted, the difference in distractor cost scores was not significant, $t(74) = 1.093$, $p = .28$, $d = 0.13$, $BF_{10} = 0.23$ again providing substantial evidence for the null hypothesis.

Overall, the results of Experiment 1 thus support our prediction that a critical factor determining distractor processing is subitizing capacity as assessed by the bifurcation point between parallel processing and serial processing. Distractor interference was significantly greater within the subitizing range of set sizes than for set sizes that were beyond an individual's capacity. Importantly the individual differences analyses further demonstrated that higher set sizes were required to reduce distractor processing for individuals with higher capacity than for those with lower capacity. Thus an individual's subitizing capacity was shown to be the crucial determinant of distractor processing at a given set size, rather than a uniform number of items across the sample.

Experiment 2

In Experiment 1 we measured enumeration performance and the subitizing range via accuracy (similarly to related prior work, e.g. Burr et al. 2010; Vetter et al. 2008) and thus used brief and masked visual displays to ensure that our procedure would be sensitive to detect an accuracy decline for increases in set size beyond a person's capacity limit. The critical prediction then concerned the effects on distractor processing measured as the cost to accuracy in the presence versus absence of the distractor. The results demonstrated both a clear bifurcation in the accuracy x set size function (distinguishing between parallel processing within capacity and serial processing beyond capacity) and importantly also confirmed our predictions that distractor costs would be observed for set sizes within a person's capacity but not for set sizes beyond their capacity. So that only a set size increase that leads to surpassing the capacity limit threshold, would also lead to a significant reduction in distractor cost, while set size increases within capacity and those beyond capacity had no effects on the distractor processing.

However, since the level of accuracy in the distractor absent conditions declined with the increased set sizes beyond capacity, as expected, this may have reduced the sensitivity to detect distractor costs for the highest set sizes, as performance approached chance levels (and participants were therefore likely to be guessing on a larger proportion of trials for these set sizes). Near-floor level performance in the distractor absent conditions, is less sensitive to reveal any further accuracy cost in the distractor present conditions.

In Experiment 2 we therefore sought to examine our hypothesis that the effects of perceptual load on distractor processing will critically depend on perceptual capacity with a different subitizing paradigm that allows for higher accuracy rates and uses a measure of RT rather than accuracy. To this purpose we modified the display and eliminated the non-target stimuli from the enumeration displays (see Figure 1b) as well as the post-stimulus mask, both changes were expected to increase accuracy even for set sizes beyond the subitizing range. We also increased the maximum set size to 12 items instead of the previous nine and used different square sizes so that participants would not be able to estimate the set size based on overall screen contrast now that there were no non-target stimuli. A conceptual replication of the same pattern of results in this variation of the subitizing paradigm would allow us to generalise our conclusions across RT and accuracy performance measures and specific variations of the task procedure (e.g. Earp & Trafimow, 2015).

Method

Participants

Once again, we approached a whole class of ~100 undergraduate psychology students to participate (but this time from a different academic year and none of the same students participated in both experiments); 87 participated in the experiment. Based on the effect sizes observed in the individual differences analyses of Experiment 1 (i.e. Cohen's $d > .5$) a sample of $n = 26$ would be necessary to achieve 80% power ($\alpha = .05$). Our sample therefore again provided good power for similar analyses to those conducted in Experiment 1. As in Experiment 1 participants were excluded if their response accuracy was below 60%

correct in the set-size 1 distractor absent condition. This led to the exclusion of 3 participants, the final sample consisted therefore of 85 participants (69 female), aged 18-21 (M =18.86, SD = 0.83).

Stimuli and Procedure

The experiment was prepared and presented in Matlab (Mathworks, Inc., Natick, MA) using the Cogent toolbox (www.vislab.ucl.ac.uk/cogent.php). Participants performed the task in individual enclosed testing cubicles containing a Dell PC and a 15-inch flat screen monitor. As in Experiment 1, a 60cm length of string was attached to the bottom of the monitor, which participants were instructed to use to establish a 60cm distance, which they maintained for the duration of the experiment.

Figure 1b illustrates an example trial. Each trial began with a fixation cross, which was presented for 1,000 ms and was followed by a stimulus display for 200ms. The stimuli to be enumerated were 1-12 white squares presented on a black background and centred on a random subset from among 20 evenly spaced positions forming an invisible ring (with a diameter of 10.9°) around the centre of the screen. In one condition the squares were all of uniform size on a given trial and constrained such that the summed overall area of the squares combined was 1.46°x 1.46, 1.94°x1.94° or 2.5°x2.5° on any given trial (i.e. the total number of white pixels on screen was the same regardless of target set size). In another condition the squares were of variable size on each trial and the combined area of the squares was not controlled; the maximum square size was 2.3° and the minimum size was 0.5°. These conditions ensured that for half of the participants the total amount of screen saturation was not a clue to the number of squares present and for half the participants the size of any individual square was not a clue to the total number. There were no non-target squares; participants enumerated all white squares on screen while ignoring the cartoon distractor. The distractor image subtended from 2.2° to 2.9° vertically by 2.2° to 2.5°horizontally and on distractor absent trials the centre of the screen was blank.

A blank screen followed immediately after the stimulus display, and persisted for up to 7,000 ms, or until a response was made. Participants were encouraged to respond as quickly as possible after seeing the stimulus. On one third of trials a cartoon distractor image was presented in the centre of the screen at the same time and for the same duration as the enumeration stimuli. Participants were instructed to respond by pressing a key on the number pad of the keyboard as in Experiment 1. The top row (‘Num Lock’, ‘/’ and ‘*’) keys were repurposed for numbers 10-12 with numbered stickers on the keys.

Target set size and the presence or absence of a distractor stimulus were counterbalanced and trials were presented in random order such that any combination was equally likely on any given trial. Following a practice block of 12 trials there were four experimental blocks of 108 trials each with a self-paced break in between blocks.

Results and Discussion

RT

RT analyses were conducted up to set size eight as in Experiment 1 (since accuracy dropped to very low levels at the higher set sizes, resulting in insufficient trials for reliable RT). Figure 5 shows the average RT for each set size, excluding trials in which RT was more than 2.5 standard deviations above the mean and trials with incorrect responses. The figure shows a transition in the performance slopes from a flat to a serial set size slope around set size three, with the slope steepening from set size five. As before the gradual steepening of the slope is likely to reflect declining numbers of individuals with a larger capacity.

The effect of set size on RT was confirmed in a one-way repeated measures ANOVA, which showed a significant effect of set size, $F(7,588) = 292.58$, $p < .001$, $\eta_p^2 = .78$. There was a significant linear effect, $F(1,84) = 367.92$, $p < .001$, $\eta_p^2 =.81$; a significant quadratic effect, $F(1,84) = 139.50$, $p< .001$, $\eta_p^2 = .62$; as well as significant cubic, fourth-order and fifth order effects (all F's > 10.52, all p's < .002).

Proportional distractor costs on RT were analysed using a repeated measures ANOVA, which revealed a significant effect of set size, $F(7,588) = 30.87$, $p < .001$, $\eta_p^2 = .27$. Pairwise comparisons with a Bonferroni-corrected alpha level of .006 (for eight comparisons), indicated that distractor effects were significantly greater than zero for set sizes one to four; set size one, $t(84) = 11.75$, $p < .001$, $d = 1.28$, $BF_{10} = 2.609e+16$; set size two, $t(84) = 15.82$, $p < .001$, $d = 1.27$, $BF_{10} = 5.593e+23$; set size three, $t(84) = 21.48$, $p < .001$. $d = 2.33$, $BF_{10} = 3.571e+32$; set size four, $t(83) = 11.57$, $p < .001$, $d = 1.26$, $BF_{10} = 1.172e+16$ (see Figure 5 bottom panel) but not for set size five, $t(84) = 1.84$, $p = .07$, $d = 0.20$, $BF_{10} = 0.60$ or six, $t(84) = 0.56$, $p = 0.58$, $d = 0.06$, $BF_{10} = 0.14$. Distractor effects were significantly lower than zero in set sizes seven $t(84) = -2.17$, $p = .03$, $d = -0.24$, $BF_{10} = 1.11$ and eight, $t(84) = -2.68$, $p = .01$, $d = -0.29$, $BF_{10} = 3.37$ but these did not survive Bonferroni correction for multiple comparisons. As in Experiment 1, these results suggest that distractors are processed within the subitizing range but not beyond, this time when distractor processing is measured as a RT cost.

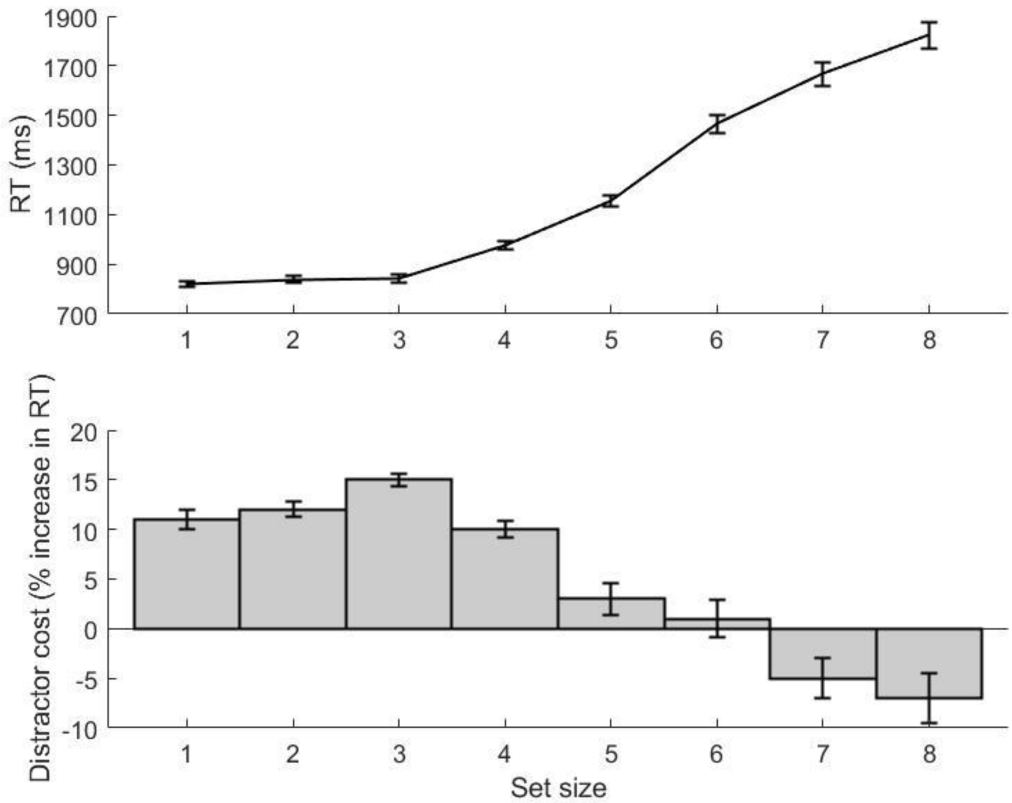

Figure 5. Top panel - RT in the distractor-absent trials as a function of set size for Experiment 2. Bottom panel - percentage distractor costs calculated as the proportional increase in RT in the distractor present condition (P) compared to the distractor absent condition (A), (i.e. P-A/A) plotted as a function of set size.

Individual differences. Next, we investigated distractor interference effects as a function of individual differences in subitizing capacity. Once again, if distractor interference depends upon available perceptual capacity then participants with greater capacity are expected to continue processing distractors at set sizes which eliminate distractor processing for lower-capacity participants.

As previously, subitizing capacity was estimated for each participant by fitting both a sigmoidal and a bilinear function, this time to the RT data in a manner similar to that in Experiment 1. Two linear components were fit to individual RT data for each set size, the first with a slope fixed at zero and the second with a positive slope, varying in steps of 10ms between -10ms and 1,000ms per item. Similarly, as in Experiment 1, the ISR calculator function described by Leibovich-Raveh et al. (2018) was used to estimate capacity based on a sigmoidal fit to the same RT data for each individual participant. The bilinear and sigmoidal functions both fit the data well (average adjusted R^2= .96, SD = .06 for the bilinear fit and R^2 = .97, SD = .04 for the sigmoid). Given the near identical fits of the two models, we used the sigmoid-based fit for consistency with Experiment 1. The average capacity limit for the sample was 3.72 (SD = 0.70, range: 1.18 – 5.28, see Figure 6).

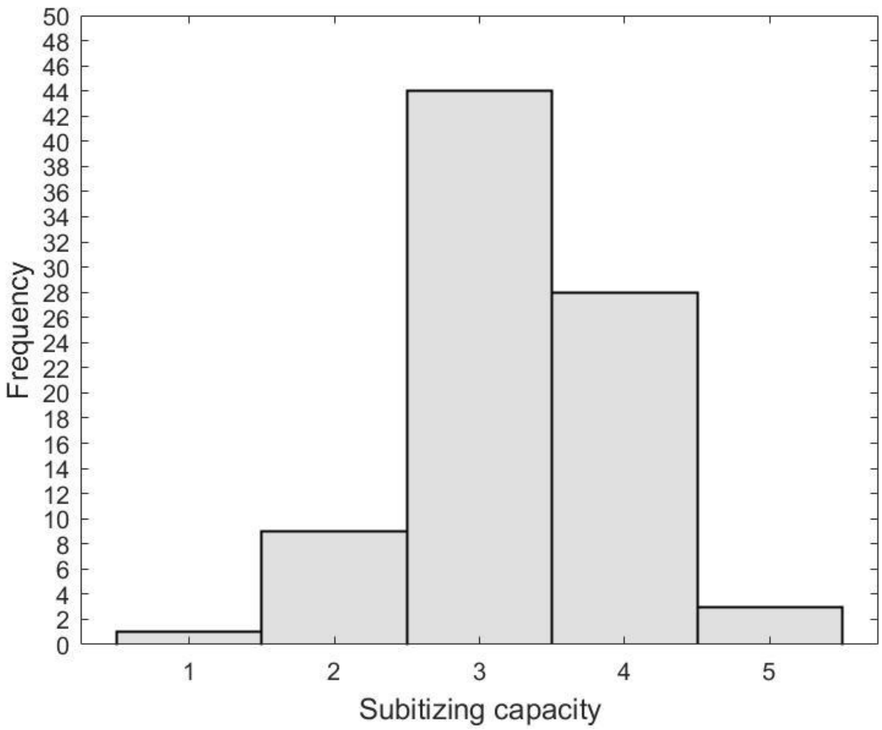

Figure 6. Histogram of subitizing capacity estimates using the sigmoidal fit fitted to RT in Experiment 2, and expressed as display set size, with capacity value binned to the lower set size integer (i.e. capacity estimates between ‘x’ and ‘x.9’ are binned within set size ‘x’).

As in Experiment 1, to test of the role of individual capacity limits, we re-ran the ANOVA of set size effects on distractor interference, this time with subitizing capacity as a covariate. The main effect of set size remained significant, $F(7, 581) = 4.84$, $p < .001$, η_p^2 = .06 and the interaction between subitizing capacity and the effect of set size was also significant, $F(7, 581) = 5.67$, $p < .001$, η_p^2 = .06 suggesting a role for capacity in determining set size effects on distractor processing.

We then compared distractor interference scores for each set size relative to the individual participant's capacity limit. As with the data from Experiment 1, we defined the first set size above a given participant's capacity estimate as the capacity 'borderline' set size (neither fully -within nor fully beyond capacity, but at the border between the two), we then took the next three set sizes below the borderline and the three set sizes above (Note 4) (Figure 7).

Table 2 presents the statistics for the comparison of distractor cost scores against zero at each set size. As can be seen, distractor interference was significantly greater than zero for within-capacity set sizes but none of the beyond-capacity set sizes, for which both Bayes factors provide substantial evidence for the null in the case of both 'borderline plus one' and 'borderline plus three' (for 'borderline plus two' set size, the Bayes factor only provides anecdotal evidence in favour of the null).

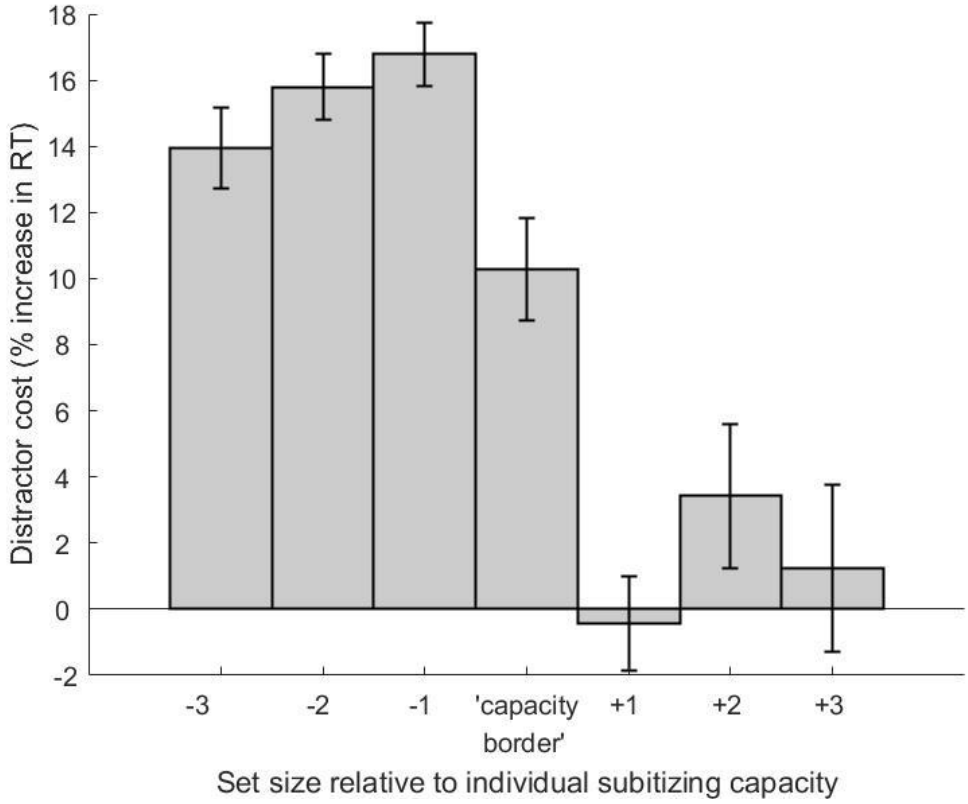

Figure 7. Mean distractor RT cost (P-A/A) as a function of set size increase or decrease relative to individual capacity estimates, error bars represent one SEM.

Table 2: Results of pairwise comparisons against zero for each capacity-relative set size in Experiment 2

Set size relative to individual capacity border	Sample size	t-test against zero	Bayes factor against zero
Border minus 3	75	$t(74) = 11.35$, $p < .001$, $d = 1.31$	BF_{10}= 7.981e+14

Border minus 2	84	t(83) = 15.71, p < .001, *d* = 1.71	BF_{10}= 2.699e+23
Border minus 1	85	t(84) = 17.33, p < .001, *d* = 1.88	BF_{10}= 1.817e+26
Border set size	85	t(84) = 6.66, p < .001, *d* = 0.72	BF_{10}= 3.969e+6
Border plus 1	85	t(84) = -0.31, p = .76, *d* = -0.03	BF_{10}= 0.13
Border plus 2	82	t(81) = 1.58, p = .12, *d* = 0.17	BF_{10}= 0.40
Border plus 3	82	t(81) = 0.49, p = .62, *d* = 0.06	BF_{10}= 0.14

Note. Set size is computed for each individual according to their individual capacity estimate.

Next, we directly compared distractor costs at the final ‘within-capacity’ set size (i.e. the capacity border set size minus one) with those at the first ‘beyond-capacity’ set size (i.e. the capacity border plus one). There was a significant difference in distractor cost, t(84) = 10.116, p < .001, *d* = 1.097, BF_{10} = 1.854e+13. In order to ensure that this difference can be attributed the transition from a set size level that is within capacity to a set size level beyond capacity (rather than mere increase in set size per se), we compared the distractor cost scores for the last-within capacity set size and the set size two steps lower (i.e. ‘capacity border minus one’ versus ‘capacity border minus two’) thus matching the step size for the previous comparison. As in Experiment 1, the difference in distractor cost scores was not significant, t(74) = -1.585, p = .117, *d* = -0.183, although the Bayes Factor fell short of supporting the null hypothesis (BF_{10} = 0.419). Similarly, for the comparison of beyond-capacity set sizes with a matched change in set size (i.e. 'borderline plus one' versus 'borderline plus three') there was no significant difference in distractor cost scores, t(81) = -0.377, p = 0.707, *d* = -0.042 and this time the Bayes factor provided substantial support for the null hypothesis BF_{10} = 0.130.

Accuracy

While Experiment 2 was designed to maximize variance due to subitizing in RT, we report parallel analyses of Accuracy data here for completeness. Table 3 presents average error-rates for each set size in Experiment 2 both for distractor present and absent trials across the whole sample. A repeated measures ANVOA of error-rates in the distractor absent condition for all set sizes except for set size 12 (to avoid end-effects) demonstrated a significant effect of set size, F(10,840) = 395.55, p < .001, η_p^2 = .825. Polynomial contrasts revealed significant linear, quadratic and cubic trends as well as a marginally significant quantic trend (p = .05).

As with previous analyses we calculated proportional distractor cost scores for each set size. These were then entered into another repeated-measures ANOVA, which revealed a significant effect of set size, F(10,830) = 5.10, p < .001, η_p^2 = .058. Follow-up t-tests demonstrated that the proportional cost scores were significantly greater than zero for set size one, t(84) = 3.45, p < .001, *d* = 0.37, BF_{10} = 26.36; set size two, t(84) = 2.84, p = .006, *d* =

0.31, BF_{10} = 4.99; set size three, t(84) = 4.20, p < .001, *d* = 0.46, BF_{10} = 288.51 and set size four, t(84) = 5.05, p < .001, *d* = 0.55, BF_{10} = 5990.21. No other cost score was significantly larger than zero [set size five, t(84) = -0.27, p = .79, *d* = -0.03, BF_{10} = 0.12; set size six, t(84) = -0.51, p = .61, *d* = -0.06, BF_{10} = 0.14; set size seven, t(84) = -1.28, p = .20, *d* = -0.14, BF_{10} = 0.26; set size eight, t(84) = -2.60, p = .01, *d* = -0.28, BF_{10} = 2.84; set size nine, t(84) = -1.70, p = .09, *d* = -0.18, BF_{10} = 0.47; set size ten, t(84) = -2.60, p = .01, *d* = -0.29, BF_{10} = 3.10; set size eleven, t(84) = 0.01, p > .99, *d* < .001, BF_{10} = 0.12; set size twelve, t(84) = -1.24, p = .22, *d* = -0.13, BF_{10} = 0.25] althoughset size eight and set size ten both had cost scores significantly below zero although these would not survive correction for multiple comparisons.

As in the analyses of RT we then re-ran the repeated measures ANOVA on distractor cost scores, this time also including individual subitizing capacity estimates (as established from RT data) as a covariate. This time, the interaction between the effect of set size and individual capacity limits was not significant, F(10,820) = 1.16, p = .315, η_p^2 = .014.

Although error rates increased with increasing set size, average performance was higher in Experiment 2 than in Experiment 1 as intended by the design of the task in this experiment. Note specifically the lower average error-rates in set sizes just beyond the average capacity limit of three to four items, for example set size five (M= 18.53% in Experiment 2 vs. 41.63% in Experiment 1) and set size six (M= 27.75% in Experiment 2 vs**.** 55.33% in Experiment 1). Given that with 12 set sizes the chance level performance was now less accurate compared to that in Experiment 1 (which had nine set sizes) this likely represents reduced rates of guessing compared to those found for Experiment 1. Table 3 also shows that performance even up to set sizes higher than the subitizing range were still highly accurate compared to Experiment 1.

These results based on response accuracy replicate the pattern for the overall sample, demonstrating significant distractor interference for set sizes within the typical 'subitizing range' of one to four items. The individual differences results established via RT (and accuracy in Experiment 1) did not replicate using error rates, which is unsurprising given that Experiment 2 was designed to maximize sensitivity to RT as a measure of capacity.

Table 3: Average error rates for each set size in Experiment 2 for distractor present and distractor absent trials

Error-rate (% errors)

Set size	**Distractor present trials**	**Distractor absent trials**
1	2.25	1.27
2	2.35	1.76
3	3.82	2.65
4	9.31	6.37
5	18.53	19.8
6	27.75	30.00
7	49.02	45.74

8	56.36	59.02
9	71.08	71.03
10	76.47	80.15
11	80.79	76.13
12	79.12	79.41

General Discussion

The present findings provide a new line of evidence for the Load Theory proposal that perceptual processing proceeds in parallel and involuntarily on all stimuli within capacity, including irrelevant distractors, by relating Load Theory to the phenomenon of subitizing. Since subitizing capacity is determined by the range of set sizes which can be enumerated in parallel, using the subitizing paradigm allowed us to assess distractor processing as a function of whether load levels were within a person's subitizing capacity or beyond it. Specifically, in two experiments, we identified each person's transition point from parallel to serial processing by means of curve-fitting. The cost to enumeration performance produced by the presence (vs. absence) of an irrelevant distractor (cartoon image) was found only when the display set sizes were within subitizing range and eliminated in displays that exceeded subitizing capacity.

This pattern of findings generalised across two different enumeration tasks. In Experiment 1 we used masked displays presenting oriented Gabor stimuli which included targets presented among visually similar non-targets (the same Gabor stimuli but with different orientation and lower contrast) and assessed subitizing capacity based on sigmoid functions for performance accuracy. In Experiment 2, we used high contrast stimuli presented without any non-target stimuli or mask and assessed capacity via sigmoid functions of performance RT. The difference in tasks was pronounced in a marked increase in performance accuracy in Experiment 2 compared to Experiment 1 (e.g. average error-rates for set sizes five and six were 19% and 28% respectively in Experiment 2, compared to 42% and 56% in Experiment 1), in line with RT paradigms, in which effects are based on the latencies of accurate responses. Irrespective of the task differences in both experiments, distractor cost depended on whether the increase in perceptual load remained within subitizing capacity or led to surpassing capacity. Distractor costs were only eliminated at the latter conditions. The findings of the same pattern results across these different tasks and performance measures therefore points clearly to subitizing capacity as the key factor, rather than any task-specific factors (such as the contrast of enumeration stimuli) or the general level of overall performance (as accuracy was higher for supra-capacity set sizes in Experiment 2, but the same pattern of results was observed).

Importantly, individual differences in subitizing capacity (as measured with the point of transition from parallel to serial enumeration) demonstrated the critical role of an individual's perceptual capacity rather than mere set size. Specifically, an increase in set size that led to a transition from 'within-capacity' to 'beyond-capacity' produced a significant reduction in distractor interference, regardless of the specific set size that was determined as the capacity limit for that participant. Conversely, an equal level of (two-item) increase in set size but between set sizes that were either both within, or both beyond, the capacity limit for a given participant, did not lead to a significant change in distractor interference. In fact, the Bayes factors for these comparisons provided evidence for the null hypotheses (i.e.

that there was no change). Furthermore, distractor interference scores within capacity were consistently significantly different from zero, whereas those for any set size beyond capacity were not. These findings thus allow us to rule out alternative accounts, which might relate individual differences in capacity and distractor processing to general task performance factors such as motivation to perform well, arousal or processing speed. These accounts cannot explain why the change in distractor processing specifically depends upon whether the set size increase was within or beyond a person's capacity.

Relation to Previous Load Theory Literature

As discussed earlier (in the General Introduction), previous support for Load Theory has primarily been derived from studies comparing processing between high and low perceptual load conditions, across various manipulations of perceptual load, that have generally either increased the number of items or features that need to be perceived in the task, or the perceptual processing requirements (e.g. conjunction vs. feature detection, e.g. Lavie, 1995) for the same number of items in the display (see Lavie, 2005; Lavie et al. 2014 for review). In such comparisons, distractor processing (as measured via interference effects or detection reports) was consistently reduced when perceptual load was increased to levels which are taken to exceed capacity limits 'universally' (i.e. across the population). Indeed, visual search studies using finer-grained manipulations of gradual increases in the search set size have demonstrated that distractor processing is only eliminated beyond set sizes of four items, and remains unaffected by gradual set size increases below this limit (e.g. Lavie & Cox, 1997; Lavie & Fox, 2000) in typical individuals (Remington et al., 2009; Remington et al., 2012) (Note 1). The present results are consistent with this previous research and significantly expand it to show that the effects of load on distractor processing depends on the individual capacity limit of participants, when this is formally defined, based on the bifurcation point in the slope of the RT/accuracy set size function. Specifically, in both of our experiments, distractors reliably caused interference to task performance within the range of set sizes which elicited a parallel slope, but not for set sizes outside this range as determined with their individual bifurcation point. In this way, the results directly support Load Theory claims that perceptual processing proceeds automatically and in parallel on all stimuli (including distractors) within capacity and extend this claim to individual differences in capacity.

Moreover, several aspects of our task design and specific pattern of the present findings provide strong evidence against other interpretations of the effects of increased set size on distractor processing, which have been previously proposed as alternative accounts to perceptual load in response competition tasks. For example, some authors (e.g. Tsal & Benoni 2010, Wilson et al., 2011) have claimed that the findings of reduced distractor effects with increased set size in letter-based response competition tasks may reflect an effect of 'dilution' of the distractor potency to trigger a competing response. This dilution effect has been proposed as an alternative account to increased demand (load) on perceptual capacity as the cause for reduced distractor processing, as the effects of increased set size were attributed to either a general effect of 'clutter' (i.e. reduced visual salience of the distractor letter due to the mere presence of added non-target letters), or feature-crosstalk (due to feature overlap between the distractor and non-target letters), or response crosstalk attributed to the response-neutral non-target letters (despite their lack of response association in the task). Although the dilution account suffers from various theoretical drawbacks (see Lavie & Torralbo, 2010 for detailed discussion), it is worth highlighting how the present results are immune to an alternative account in terms of distractor dilution, and instead strongly tie the effect of set size on distractor processing to the demand on perceptual capacity. Firstly, our measure of distractor effects was from a large and colorful distractor image that was presented at fixation, had little feature overlap with the task letters, and was not associated with any related task response. Therefore, the distractor processing in our task was unlikely to have suffered from either response or feature crosstalk, nor from a general effect of clutter by the added small white squares or oriented gratings with increased set size. Secondly, while dilution simply relates to increased set size, our perceptual capacity account is based on specifically relating set size to the level of demand on a person's limited capacity. Indeed, our use of a formal definition for capacity limit on the basis of the highest set size that could be processed in parallel (as indicated by a flat enumeration slope before the bifurcation point), allowed us to make clear a-priori predictions, namely, that only set size increases from levels that are within capacity to levels that surpass capacity should reduce distractor processing. The findings that the effects of set size on distractor processing significantly interacted with subitizing capacity (in our ANCOVA analyses), such that the very same step increase in set size only reduced distractor processing when the increase paralleled the transition from within- to beyond capacity, but not when the increase is between two set sizes that are either both within-capacity or both beyond-capacity, confirmed our predictions. Similarly, our individual differences results also clearly demonstrated that whether or not the distractor was perceived in a particular set size critically depended on whether it was within or beyond their individual capacity. All these findings cannot be explained by dilution, since the crux of the difference to load, that all dilution accounts share, is that the distractor effect is diluted with increased set size by factors that do not reflect load on perceptual capacity.

Another aspect of the present research was that the set sizes were presented randomly within a block of trials. Thus, any effects found cannot be attributed to a strategic effect of 'attentional set', for example people adopting wider attentional 'zoom' when anticipating low load, and narrower zoom when anticipating high perceptual load. These accounts have been previously proposed in studies manipulating perceptual load in a blocked-design (e.g. Theeuwes et al., 2004, Chen and Cave, 2016). Since no pre-cuing was involved in our study either, participants could not adopt a wide or narrow zoom in advance of each display (c.f. Chen & Cave, 2013). Our study procedure made it also unlikely that people would adopt a different attentional zoom instantly upon the display presentation, and specifically that a narrow zoom that excludes the distractor region, would only be adopted upon presentation of the set sizes beyond capacity. This is because not only did we use brief display presentations, but also the probability of a narrow spatial layout of items was in fact lower for the larger set sizes in our task, which have occupied a larger spatial region (given that all circle positions were equally as likely for all set sizes). Finally, since the effects of load on distractor processing clearly depended on perceptual capacity in our study, only a capacity based-zoom account can be proposed to account for our results. For example, such an account may suggest that the transition to a more demanding enumeration process in set sizes that lie beyond a person's subitizing capacity pulled resources into a narrower spatial region, which is thus more likely to preclude distractor regions. We note however that a spatial restriction of focus is not included in any of the prevailing accounts for enumeration processes beyond the subitizing range, as long as a serial counting process is prevented (with brief displays; Burr, Turi & Anobile, 2010; Leibovich-Raveh et al. 2018). We also note that because this account attributes the zoom region to the level of demand (i.e. load) on a limited perceptual capacity, it does not constitute an alternative account to the Load Theory model, but instead makes a specific suggestion for how resources are pulled away from distractors with higher load. Future research employing orthogonal manipulations of zoom-related factors (e.g. manipulating the distance between the distractor and task-relevant items) and set size within the current paradigm may prove interesting.

Finally, a resource-based account of the effects observed here and in previous load research (as opposed to the attentional settings-based, or dilution accounts) lends itself to a comprehensive model which also delineates the neural mechanism involved. Indeed, Bruckmaier et al. (2020) have recently demonstrated that perceptual load effects can be directly attributed to the level of demand on neural metabolism (as measured with spectroscopy tracking of the levels of the intracellular metabolic enzyme cytochrome c oxidase). Their findings demonstrated a load-dependent metabolism trade-off between attended and unattended processing in visual cortex. Specifically increased perceptual load led to increased level of neural metabolism subserving attended processing, accompanied by a proportional reduction in metabolism levels mediating unattended processing. Moreover, since the neural metabolism trade-off was shown in occipital visual cortex regions including both extrastriate and striate regions, they allow attribution of behavioural results suggesting the unattended distractors were not perceived in tasks of high perceptual load to a shortage in the metabolic resources required for visual cortex to respond to an unattended stimulus, when the relevant task demands greater neural activity.

While such an account will attribute the reduced distractor interference effects to reduced perceptual processing of the distractor with high perceptual load that exceeds limited resources, our implicit measures of distractor processing (based on a cost in task RT or accuracy) do not allow us to draw any direct conclusions about distractor perception. A large body of previous research has established that increased perceptual load in the task leads to increased incidence of inattentional blindness, broader psychophysical tuning functions (indicating reduced perceptual precision) and reduced detection sensitivity for stimuli outside the focus of attention (e.g. Cartwright-Finch & Lavie, 2007; Macdonald & Lavie, 2008; Carmel et al. 2011; Stolte et al. 2014; Lavie et al. 2014). Moreover, some research has extended this pattern to show reduced recognition of salient yet entirely irrelevant distractor faces presented at fixation (Jenkins et al. 2012) under high perceptual load in the task. An important direction for future research would therefore be to employ similar explicit measures of distractor perception within our new paradigm to directly attribute our effects to perceptual processing.

Relation to Prior Subitizing Literature

The present results also provide a new line of support for a growing body of literature which, while accepting that subitizing is a parallel process nevertheless demonstrates that it depends on the availability of attentional resources (Burr et al., 2010). One line of previous research highlighting the importance of attention for subitizing has demonstrated that subitizing cannot occur during the attentional blink (AB; Burr et al. 2010; Egeth et al. 2008; Olivers & Watson, 2008; Xu & Liu, 2008), when attentional resources are occupied by processing related to a prior stimulus. Other studies have shown that stimuli presented concurrently during a task of high perceptual load are less likely to be subitized. These studies utilised dual-task paradigms in which participants were instructed to enumerate peripheral stimuli as a secondary task while performing a concurrent primary task that places varying demand on attention (Burr et al., 2010; Chesney & Haladjian, 2011;

Vetter et al., 2008). For example, Chesney and Haladjian (2011) found that when participants performed an object tracking task, their capacity to subitize additional stimuli was reduced in a one to one ratio between the primary object tracking task and the subitizing task. That is, for each additional item that the participant was required to attentively track on-screen, their subitizing capacity was reduced by one. A similar relationship was also observed in visual short-term memory, wherein participants were able to subitize fewer stimuli presented during the delay period of a visual working memory task as the working memory load was increased in the task (Piazza et al., 2011).

Similarly, in two lines of study by Vetter et al. (2008) and Burr et al. (2010) a task in which participants attempted to identify targets was presented as the primary central task while participants were also asked to enumerate secondary target stimuli presented in a ring around the central stimulus. When the central task placed minimal demands upon attention (a simple feature detection task), subitizing of the peripheral stimuli was unaffected. However, when the central task involved greater attentional demands (discrimination of a conjunction of colour and orientation) subitizing was impaired.

Our expansion into a measures of subitizing capacity as assessed with the bifurcation of the RT or Error rate x set size function, (rather than the general impact on task performance) allows us to further attribute the effects to the level of shared demand between enumeration and other processes of visual perception. Moreover, by using a selective attention paradigm, (in contrast to the previous studies’ use of a dual task paradigm) the present results are immune to alternative accounts that may attribute the effects of increased task demands and the accompanied slowing in RT to memory degradation, or deprioritization of the secondary task response, rather than reduced perception

Finally, our selective attention measure of the level of interference by an entirely task-irrelevant distractor demonstrates a novel implication of a person's subitizing capability for their ability to focus attention, namely that people with a greater subitizing capacity are susceptible to distractor processing in a greater range of display set sizes compared to people with a lower subitizing capacity.

Relation to Previous Individual and Group Differences Research

Recent evidence suggests that a shared resource underlies individual differences in subitizing and perceptual detection abilities such as those measured in change blindness, inattentional blindness, and motion tracking (Eayrs & Lavie, 2018; 2019). Subitizing and these task measures of perceptual detection abilities were shown to load upon a common factor, which was distinct from the capacity for working memory tasks that demanded on executive resources. Furthermore, perceptual capacity was associated with grey matter density in right posterior parietal cortex, whereas working memory executive control capacity was associated with grey matter density in left middle frontal cortex. Taken together with the present results, these studies support the conclusion that individual differences in perceptual capacity are an important determinant of both stimulus detection and distractor processing as predicted by Load Theory (which suggests that both processes depend on the availability of perceptual capacity rather than voluntary top-down executive control goal (to detect, or ignore, these stimuli).

Some research manipulating gradual increases in perceptual load (in visual search and line judgement tasks) has demonstrated that individuals with Autism Spectrum Disorder

(ASD) have a larger perceptual capacity than age and IQ matched neurotypical controls. For example, Remington et al. (2009) found that individuals with an ASD diagnosis processed distractor stimuli under conditions of load which exhausted the capacity of non-ASD participants. Similarly, individuals with ASD were either less susceptible to load-induced inattentional blindness phenomena, or required a higher level of load than those needed to elicit reduced detection of stimuli outside the focus of attention compared to the neurotypical controls (Remington et al., 2012; Swettenham et al., 2014). Similar effects have also been observed in individuals who exhibit Autism-related traits within the neurotypical population (Bayliss & Kritikos, 2011).

If subitizing represents perceptual capacity as we claim, then this leads to the prediction that subitizing capacity should be increased for Autistic individuals. However, deficits in holistic-global versus local processing strategies in Autism as well as verbal enumeration deficits (e.g. the ease of linking quantity with the verbal number label) complicate a clear test of this prediction (see for example the steep subitizing slopes reported in O’Hearn et al. 2013).

A parallel strand of research has demonstrated that there are significant age-related differences in the effects of perceptual load, with children and older adults both exhibiting reduced capacity relative to mature young adults. That is, smaller set sizes were sufficient to reduce distractor processing in older people and children in a similar manner to the low-capacity groups in the present experiments (Huang-Pollock et al., 2002; Maylor & Lavie, 1998). Further research also extended this to measures of subjective awareness, demonstrating that children and adolescents are more susceptible to inattentional blindness with smaller increases in perceptual load compared to those needed to induce the same rate of inattentional blindness in adults (Remington et al., 2014). The present results suggest that similar effects could be observed if perceptual capacity was measured via the subitizing paradigm so that age related changes in subitizing capacity (e.g. Arp et al. 2006; Starkey & Cooper, 1995; Svenson & Sjöberg, 1983; Trick et al. 1996; Watson et al. 2007) would result in similar impact on distractor processing and rates of inattentional blindness.

Finally, there is now also substantial evidence that perceptual capacity can be enhanced by experience playing action video-games (Dye et al., 2009; Green & Bavelier, 2006) and this has been extended to subitizing capacity too. For example, Green and Bavelier (2006) found that subitizing capacity as well as the closely related object tracking capacity (MOT) were both enhanced in a sample of action video-game players relative to non-gaming controls. Importantly, an intervention study established a causal effect of gaming on capacity, with significant increases in subitizing range and tracking capacities after only 10 hours of experience with action games. Furthermore, Dye et al. (2006) also demonstrated significantly increased interference from flanking distractors in action gamers relative to controls, suggesting that their increased capacity leads to increased spill-over to distractor processing, exactly in line with the results of the present investigation.

Conclusion

In conclusion, by relating Load Theory to subitizing we obtained new evidence for its fundamental claims that perceptual processing has limited capacity but proceeds in parallel on all stimuli within capacity, including irrelevant distractors. Despite the distractor stimuli being entirely task-irrelevant, they still caused interference to task performance, but only in task conditions of lower perceptual load that were associated with a parallel enumeration, while distractor processing was eliminated beyond the point of transition to a serial slope.

Moreover, individual differences in the parallel to serial transition point showed that higher capacity was associated with distractor processing at larger set sizes compared to lower capacity, since these were within the parallel processing range for the high but not low capacity individuals. These results extend Load Theory to another demonstration of the critical role of perceptual load in determining irrelevant distractor processing across to a novel task. Importantly, by using the subitizing paradigm we could directly link the Load Theory claim of parallel processing within capacity (as shown with the error rate x set size slope) to the theory claim of involuntary processing within capacity. Thus, our findings that the critical factor determining distractor processing was the point of transition from parallel to serial slope (across different task performance measures) rather than set size per se, provides a novel line of support for the role of attention in perceptual processing proposed in Load Theory. The findings also provide novel evidence in support of the idea that the subitizing phenomenon represents a task-general capacity limit on attentional processing (Eayrs & Lavie, 2018; 2019; Mazza & Caramazza, 2015).

Footnotes

Note 1. As per Lavie's original definition of perceptual load and in line with the limited resource approach in Load Theory (e.g., Lavie & Tsal, 1994; Lavie, 1995) the precise set size that should exhaust capacity is of course expected to vary in line with the perceptual processing requirements of the task (see Lavie, 1995 for discussion and for the first demonstration that set sizes of just one or two relevant items can exhaust capacity with increased complexity of the discrimination task). In the case of visual search given the important role of items similarity and their heterogeneity (see Duncan & Humphreys, 1989; Roper et al. 2013) this of course means that stimulus variation along these dimensions would modify the specific level of set size that can be accommodated within capacity within each search paradigm.

Note 2. Set size nine was excluded from all analyses to avoid 'end effects' caused by participants guessing the maximum set size in the very large set sizes

Note 3. For participants with capacity estimates below three or above five there were not enough trials for the within or beyond capacity set sizes (e.g. for a capacity estimate of 2.3 set size 3 is borderline set size and there are no trials for borderline minus 3). These participants were excluded from any comparisons that required such set sizes, and the final sample sizes are indicated in Table 1)

Note 4. As in Experiment 1 this led to the exclusion of participants with very low or very high capacities from the 'minus three' and 'plus three' comparisons, specifically nine participants who had capacity estimates lower than three items and three who had a capacity greater than five

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