American Psychological Association

Journal of Experimental Psychology: Human Perception and Performance

0096-1523/18/$12.00

2018, Vol. 44, No. 8, 1240–1257
http://dx.doi.org/10.1037/xhp0000530

Establishing Individual Differences in Perceptual Capacity

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Limited capacity for visual perception results in various "inattentional blindness" phenomena across a wide variety of manipulations that load perception. Here, we propose that these phenomena are mediated by an underlying generalized capacity for visual perception, which also underlies subitizing: the ability to enumerate a limited number of items in parallel from a brief exposure. We tested this proposal by examining whether individual differences reveal common intraindividual variance between measures of visual perception as well as of subitizing capacity. Visual perception was measured in change blindness (Rensink, O'Regan, & Clark, 1997), load-induced blindness (Macdonald & Lavie, 2008), and multiple object tracking tasks. Subitizing capacity was measured as the number of items that could be reported in parallel in an enumeration task. Perceptual capacity as indexed by subitizing was consistently a unique predictor of performance in change blindness, load-induced blindness, and motion tracking beyond any general factors that apply to both subitizing and estimation of larger set sizes. Moreover, when measures of working memory were included, factor analysis indicated two orthogonal factors: perceptual and working memory. Overall, the results support the hypothesis of a generalized capacity for visual perception, and establish subitizing capacity as a predictor of individual susceptibility to inattentional blindness under load.

Public Significance Statement

People have limited capacity for perception and will often fail to notice objects outside their focus of attention, exhibiting a form of "inattentional blindness." However, some people may have superior (whereas others have inferior) visual detection abilities. This study establishes a new measure that can predict a person's capacity for visual perception and object detection across multiple tasks. Results using this measure show that people who can instantly enumerate a greater number of items are found to be less prone to inattentional blindness: They can more accurately detect unattended items, changes in complex scenes, and track more moving objects compared with people with a smaller enumeration capacity. These findings establish a new concept of generalized capacity for visual perception and awareness, and provide the scientific basis for new tests that can be applied for operator screening or selection for training in many safety-critical operations (e.g., defense operators, Closed Circuit Television Monitoring (CCTV), airport security).

Keywords: attention, perceptual capacity, subitizing, inattentional blindness, change blindness

What are the limits of our capacity to be visually aware of the world around us? This important question has stirred much interest over the years, ever since the seminal study by Neisser and colleagues (e.g., Neisser, 1979; Neisser & Becklen, 1975) demonstrated that people can fail to notice highly conspicuous events, such as a woman walking with an open umbrella across their field of view, when they focus attention on another event (e.g., people playing a ball game).

Limits on Visual Perception and Awareness: "Inattentional Blindness"

Demonstrations of people's limited capacity for visual perception come from a variety of more recent paradigms. Perhaps the most prominent of these is the inattentional blindness paradigm. In a typical inattentional blindness task, people are asked whether they noticed an unexpected and task-unrelated stimulus that is presented once at the very end of the task (e.g., Cartwright-Finch & Lavie, 2007; Mack & Rock, 1998; Simons & Chabris, 1999). Importantly, the unexpected nature of the stimulus is not critical for inattentional blindness to occur. This is shown in a load-induced blindness paradigm (e.g., Carmel, Thorne, Rees, & Lavie, 2011; Macdonald & Lavie, 2008; Ward & Scholl, 2015), in which people are explicitly asked to detect the occasional appearance of

This article was published Online First March 26, 2018.

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This work was supported in part by the Ministry of Defense, Defense Science and Technology Laboratory. We thank the London Science Museum for the opportunity and facilities for data collection, and Anders Jespersen, Danielle Bagri, and Madeleine Payne for their assistance in data collection at the museum.

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a stimulus outside their attention focus, yet they still experience "blindness" in conditions of high perceptual load in the attended task. Similarly, in the change blindness paradigm (e.g., Beck, Rees, Frith, & Lavie, 2001; Lavie, Beck, & Konstantinou, 2014; Rensink, O'Regan, & Clark, 1997), people often fail to detect changes between stimuli across some visual disruption (e.g., in the form of a flicker) despite actively searching for them. The visual disruption does not interfere with the visibility of the change, but instead interferes with attention capture by the large transient signal that the change otherwise involves. In all of these tasks, observers are found to be strikingly unaware of stimuli and changes outside their focus of attention despite them being clearly visible. However, different task conditions can lead to different rates of inattentional blindness or change blindness, and even under the same task conditions, not all people suffer from inattentional blindness or change blindness to the same degree.

A major factor determining the rates of perception failures in these paradigms is the level of perceptual load in the attended task. Perceptual load has been operationally defined by referring either to the number of task units (e.g., different identity letters in a letter search task) or the level of perceptual demand (e.g., its complexity) the task requires for the same number of units (see Lavie, 1995; Lavie & Tsal, 1994). Higher perceptual load, so defined (e.g., search tasks of larger set sizes or those requiring more complex perceptual discriminations of conjunctions of color and shape rather than just single color detection), was found to result in increased rates of change blindness, inattentional blindness, and load-induced blindness for unattended stimuli (e.g., Carmel et al., 2011; Konstantinou & Lavie, 2013; Lavie, 2006; Lavie et al., 2014; Macdonald & Lavie, 2008; Remington, Cartwright-Finch, & Lavie, 2014). Furthermore measures of detection sensitivity in these paradigms confirmed that "blindness" reports reflected reduction in sensitivity of perception for unattended stimuli under high load in the task rather than an effect of response criterion.

Importantly, these findings have been replicated with a variety of perceptual load manipulations, which all converge to show reduced perception accompanied by reduced visual cortex responses to unattended stimuli, under conditions of high perceptual load in the attended tasks (e.g., Bahrami, Lavie, & Rees, 2007; Rees, Frith, & Lavie, 1997; Vuilleumier, Schwartz, Duhoux, Dolan, & Driver, 2005; see Lavie, 2005; Lavie et al., 2014; Lavie & Torralbo, 2010, for reviews). Indeed, in some cases, high perceptual load has been shown to eliminate noticing of any task-unrelated stimuli across the entire sample (Cartwright-Finch & Lavie, 2007).

All of these findings suggest a generalized limit to the capacity for visual perception, which, when fully consumed with a high-load task, results in "blindness" elsewhere. Crucially, perceptual load does not simply correspond to general cognitive load but rather to specific demands on perceptual processing. Manipulations of nonperceptual "cognitive control" load, for example, increased working memory load, can have similar effect on task difficulty as perceptual load but lead to opposite effects on distractor processing to those of perceptual load (e.g., Carmel, Fairnie, & Lavie, 2012; de Fockert, Rees, Frith, & Lavie, 2001; Lavie, 2000; Lavie, Hirst, de Fockert, & Viding, 2004). Thus, perceptual capacity is a distinct construct from working memory and other cognitive control functions involved in the prioritizing of different task stimuli (e.g., in primary vs. secondary tasks; see Brand-D'Abrescia & Lavie, 2008; Lavie et al., 2004).

The purpose of the present study was to further characterize perceptual capacity as distinct from working memory and other more general cognitive capacities, using an individual differences approach. Thus, instead of manipulating the task conditions that result in blindness across the sample, we assessed the differences in the rates of blindness for a fixed level of load across different loading tasks. To test the generality of capacity limits for visual perception, we included a measure based on "subitizing": the ability to accurately report the number of items from very brief display presentations (lasting a fraction of a second) in addition to more traditional visual perception tasks. We related subitizing to visual detection performance in three different tasks—change blindness, load-induced blindness, and multiple object tracking (MOT)—by assessing interindividual covariance in subitizing and detection performance in these tasks. We therefore investigated the generalized capacity for perception across diverse task demands. Establishing measures of perceptual capacity and relating these to subitizing also allows prediction of an individual's visual detection ability, and, conversely, their propensity for inattentional blindness, by a brief and simple-to-administer measurement of their ability to count items from a brief display.

Subitizing and Perceptual Capacity: Previous Research

Although subitizing has typically been studied within the domain of enumeration, we reasoned that it should reflect more generalized visual detection and discrimination abilities, as it requires rapid detection and individuation of items simultaneously presented for a very brief duration. Indeed, in an enumeration task, responses (accuracy or reaction times [RTs]) typically form a characteristic set size function consisting of two linear components: a very shallow or flat slope, which then bifurcates at a small number of items into a serial slope as set size increases further (Kaufman, Lord, Reese, & Volkmann, 1949). The encoding of sets before the bifurcation point is thus thought to be simultaneous and parallel (as we would expect for encoding of items within perceptual capacity); serial processing then becomes necessary when the capacity for this parallel processing is exhausted (Trick & Pylyshyn, 1993, 1994). Note that although subitizing capacity is quantified by set size and reported simply as the number of items that can be subitized, this limit is not a limit on counting ability as such. Clearly, people are able to count large numbers of items in a serial manner. The limit is rather in the simultaneous, parallel processing capacity for detection and individuation of items (see Ester, Drew, Klee, Vogel, & Awh, 2012; Piazza, Fumarola, Chinello, & Melcher, 2011).

In support of our hypothesis, estimates of subitizing capacity across the population suggest limited capacity of circa four items, and these are similar to capacity limits estimated in previous perceptual load research. For example, Lavie and colleagues have demonstrated, on multiple occasions, that search tasks that involve four task-relevant items or fewer do not exhaust perceptual capacity, whereas larger sets do (Forster & Lavie, 2008; Lavie & Cox, 1997; Lavie & Fox, 2000). Finally, as we briefly review here, a few recent studies of subitizing are suggestive of a link with visual perception capacity in support of our hypothesis.

Several studies have related subitizing to attention and capacity-limited visual perception using the attentional blink paradigm. In this paradigm, several stimuli are presented in rapid succession. Stimuli presented within 700 ms of a target in this stream are less likely to be detected or recognized, and this is attributed to attentional resources still being occupied by the target (Raymond, Shapiro, & Arnell, 1992). When enumeration stimuli are presented in the post target blink period, subitizing performance is significantly diminished (compared with their presentation with no preceding target; e.g., Burr, Turi, & Anobile, 2010; Egeth, Leonard, & Palomares, 2008; Olivers & Watson, 2008; Xu & Liu, 2008).

In other attention tasks, subitizing was significantly worse when attention was directed toward a spatially (rather than temporally, as in the attentional blink paradigm) separate task. For example, in a study by Railo, Koivisto, Revonsuo, and Hannula (2008), subitizing performance was significantly worse for unexpected dots appearing while participants were attending a line-length judgment task similar to that used by Mack and Rock (1998) to assess inattentional blindness.

Subitizing has also been shown to be significantly affected by the level of perceptual load in a concurrent task. For example, in a study by Vetter, Butterworth, and Bahrami (2008), participants performed an enumeration task concurrently with a primary task of either low or high perceptual load. Their participants discriminated target shapes presented at fixation. The targets were defined by either a single feature (color, low perceptual load) or a conjunction of features (color and orientation, high load). Participants also attempted to enumerate the number of stimuli in a surrounding circle. High perceptual load in the central task reduced subitizing performance for the peripheral stimuli. Similarly, Chesney and Haladjian (2011) showed that while tracking multiple moving dots, the capacity for subitizing squares that were presented briefly among the dots was reduced proportionally to the number of objects being tracked. In their study, the average subitizing capacity decreased by approximately one item for every dot that was being tracked, suggesting that the same capacity limit underlies both tasks. In contrast to these findings, concurrent "complex span" working memory load does not impact on subitizing performance but does have a detrimental effect on enumeration of higher quantities (Tuholski, Engle, & Baylis, 2001), thus providing further evidence that the capacity limit underlying subitizing per se (as opposed to enumeration in general) is specific to perceptual processing.

In summary, the findings of previous research are encouraging for the hypothesis that there is a general perceptual capacity limit that underlies subitizing and detection in attention-demanding task conditions. In the present research, we investigate this further by assessing common variance across diverse task demands in the change blindness, load-induced blindness, MOT, and subitizing paradigms.

Study 1

The aim of Study 1 was to assess whether individual differences in detection of change between two flickering images can be predicted from perceptual capacity as measured by subitizing performance. To measure subitizing capacity, participants performed a canonical enumeration task with brief stimulus presentations. The enumeration task required participants to rapidly estimate and report the number of a briefly presented set of squares (see Figure 1). The point at which the report-accuracy/set-size function transitioned from parallel to serial was taken as their maximal subitizing capacity. Change detection was measured using the flicker task, which is perhaps the best established measure of the phenomenon of change blindness (Rensink et al., 1997). Participants were asked to detect the presence or absence of a change in flickering pairs of images of a real-world scene (see Figure 2). If a common capacity limit underlies both subitizing and change detection, there should be a positive association between subitizing capacity and the ability to detect the presence of changes.

Method

Participants. A sample of 296 participants (132 male), aged 18 to 64 years ($M = 31.33$, $SD = 13.34$), volunteered to participate in Study 1. Participants did not receive financial compensation for their time. Participants' data were excluded from analysis if they performed at chance-level accuracy in the lowest set size of the enumeration task (11 participants), or if their false alarm rate was more than two standard deviations above the group average in the change detection task (six additional participants). The final sample analyzed was therefore 279 (127 male), aged 18 to 64 years ($M = 30.40$, $SD = 12.07$).

Stimuli and procedure. The data were collected in the "Live Science" exhibition at the Science Museum in London over a period of several consecutive weeks. All participants provided written informed consent and had normal or corrected-to-normal

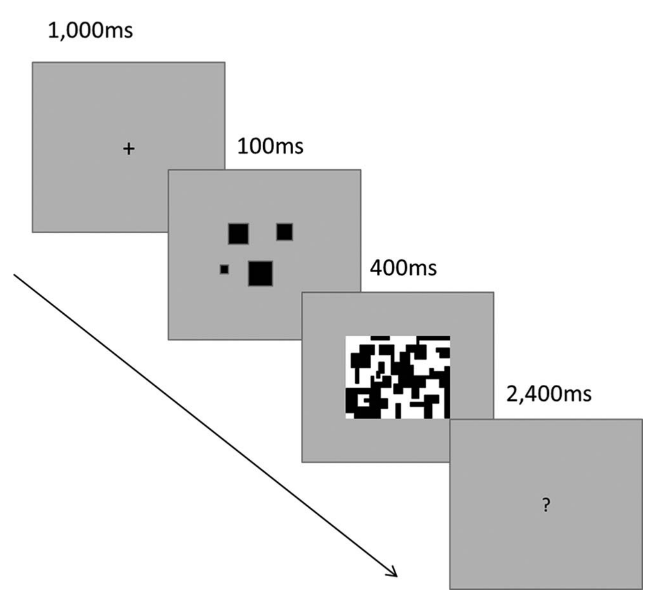

Figure 1. The enumeration task used in both Studies 1 and 2. A fixation cross was presented for 1 s, which was then replaced by a display containing a variable number of (1–9) randomly sized and positioned squares. After 100 ms, the stimulus display was replaced by a black-and-white noise mask for 400 ms and then a central "?" for 2,400 ms. Participants were instructed to respond as quickly as possible after the squares were presented, indicating how many they thought there were by pressing the corresponding key on the keyboard number pad.

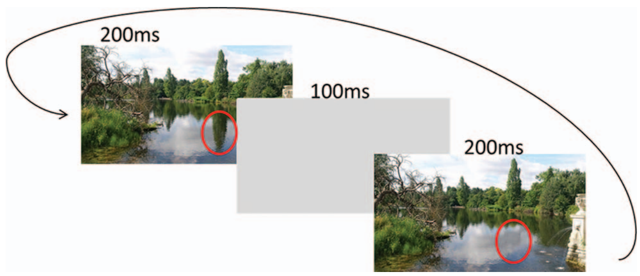

Figure 2. The change detection task used in Study 1. A photographic image of a real-world scene was presented for 200 ms, followed immediately by a gray rectangle of matching size and position, and then another scene image for 200 ms, creating the appearance of a "flickering" image. This stimulus cycle repeated for up to 15 s until the participant responded by pressing either the left or right "shift" key to indicate whether both images were identical or not, respectively. See the online article for the color version of this figure.

vision. The study was conducted in a quiet section of the museum; this area contained three computers, and so volunteers participated in groups of one to three at a time. There was always at least one experimenter present during the study; after explaining the task and obtaining informed consent, the experimenter initiated the tasks. Tasks were prepared and presented in MATLAB (MathWorks, Inc., Natick, MA) using the Cogent toolbox (www.vislab.ucl.ac.uk/cogent.php). Participants were seated approximately 60 cm from the screen and asked to maintain this distance, but their head position was not restrained. The entire study took approximately 25 min to complete.

Enumeration task. Figure 1 illustrates a typical enumeration trial. Each trial began with the presentation of a fixation point for 1 s; this was followed by a stimulus set of black squares, presented for 100 ms, each of which was randomly positioned in an area subtending 7.5 cm × 7.5 cm (7.15° × 7.15° at a distance of 60 cm) in the center of the screen. The squares varied in size, ranging from a minimum of 0.4 cm to a maximum of 4.0 cm (0.38° to 3.8° at a distance of 60 cm). The stimulus display was followed immediately by a central noise mask made up of randomly positioned black-and-white squares covering the same area as the stimulus display (7.5 cm × 7.5 cm). After 400 ms, the mask was replaced by a central "?" to prompt a response; this remained onscreen for an additional 2,400 ms or until a response was made. Participants were instructed to respond as quickly as possible indicating the number of squares displayed by pressing a key from 1 to 9 on the right-hand number pad of the keyboard. They could respond at any time following the initial stimulus display.

The task comprised of one practice block of six trials, followed by three experimental blocks of 54 trials each. After the task was explained to them, participants completed the practice block and confirmed that they understood the instructions before continuing to the experimental trials.

Change detection task. Each trial began with a fixation point for 1 s, which was followed by the presentation of a photograph of an outdoor scene occupying a space 22.5 cm × 13.52 cm (21.2° × 12.8° at a distance of 60 cm). The image was presented for 200 ms, followed by a gray rectangle of matching dimensions for 100 ms, and then by a second image for an additional 200 ms, which was again replaced by a gray rectangle presented for 100 ms (see Figure 2). The stimuli cycled repeatedly in this fashion for a maximum of 15 s or until participants responded. After a response was made, a green tick (3.1 cm × 3.82 cm) or a red cross (2.5 cm × 2.5 cm) appeared onscreen for 700 ms, indicating that the response was correct or incorrect, respectively.

The scene stimuli could either be identical (50% of trials) or could contain a slight but conspicuous change (50% of trials). Participants were instructed to respond by pressing the right shift key on the computer keyboard if a change was present, or the left shift key if there was no change. They were instructed to respond as soon as they thought they knew the answer; if the 15 s expired with no response being made, a "no change" response was recorded.

The task consisted of 44 trials in total, each of which was initiated by the participant by pressing the space bar when they were ready. After the task was explained to them, participants completed one demonstration practice and then commenced the experimental trials.

Results

Change detection task performance. Table 1 presents average change detection performance for the entire sample. As shown in the table, the false alarm rate was very low (as is typical in change blindness paradigms); a nonparametric estimate of detection sensitivity ("A") was therefore calculated using the formula described by Zhang and Mueller (2005). The associated measure of decision bias (b) was also calculated. These measures were used in subsequent analyses.

Enumeration task performance. A curve-fitting procedure was used to estimate individual subitizing capacity. Each participant's accuracy (% correct) at each set size from 1 to 8 was fit with a bilinear function.[1] The function consisted of two linear components fitted to the enumeration accuracy data for each participant as follows: The function used starting values of 90% intercept and 0% slope of the first line, and −15% for the slope of the second line. Each integer set size value was tested as a candidate breakpoint for the function using these starting values. The value that fit with the least error was then taken as a starting point, and parameters were varied from −1 to +1 of that value using MATLAB's fminsearch function to find the best-fitting slope and intercepts. The average fit of the function to the enumeration data was good. Across the sample, the average root mean square error (RMSE) was 8.02 (SD = 4.39) and the average adjusted R-squared value was 0.78 (SD = .20). Thus, the bilinear function appears to predict the observed scores with little error.

The mean estimated subitizing capacity was 3.63 (SD = 0.92), which fits well with typically observed limit of three to four items in similar tasks that involve very brief display durations (e.g., Burr et al., 2010). As a measure of performance not dependent upon subitizing capacity (i.e., "estimation" performance), the average accuracy across all set sizes above the bifurcation point was calculated for each participant. The sample mean estimation accuracy was 46.02% (SD = 10.91).

[1] Set Size 9 was excluded from analysis because of "end effects" observed in previous research, wherein participants tend to guess the maximum value when presented with large set sizes; artificially inflating the number of correct responses.

Table 1
Average Performance in the Change Detection Task of Study 1

Measure	Mean	*SD*
Detection rate	.68	.13
False alarm rate	.44	.06
Detection sensitivity (A)	.89	.06
Response bias (b)	1.99	.49

Table 3
Hierarchical Regression Predicting Change Detection Rates From Subitizing (Step 2) While Controlling for Estimation Accuracy (Step 1)

Model	Predictor	β	*t*	*p*
Step 1	Constant		37.79	<.001
Adjusted R^2 = .02, p = .013	Estimation	.24	2.49	.013
Step 2	Constant		11.57	<.001
Adjusted R^2 = .14, p < .001	Estimation	.24	4.12	<.001
	Subitizing	.36	6.35	<.001

Detection rate. Table 2 presents the correlation matrix for all the variables measured in Study 1. Subitizing capacity was significantly correlated with change detection rate, $r(278) = .31$, $p < .001$: Individuals who could subitize more items were more likely to accurately detect changes. There was also a correlation between change detection rate and estimation accuracy, $r(278) = .15$, $p = .013$, which was significantly weaker than that between subitizing and detection rate (difference z score $= -2.24$, $p = .03$; calculated using the method described by Hittner, May, & Silver, 2003, and implemented using the cocor package [Diedenhofen & Musch, 2015] in R [R core team, 2013]).

A hierarchical regression was used to examine the unique contribution of subitizing capacity to change detection when including estimation accuracy to control for general factors. The regression included two steps, the first of which included only estimation accuracy as a predictor of detection rate; subitizing capacity was then added to the model in a second step. Both steps were significant (Step 1: adjusted $R^2 = .02$, $p = .013$; Step 2: adjusted $R^2 = .14$, $p < .001$), and both subitizing capacity and estimation accuracy accounted for a significant portion of unique variance in the final model (as shown in Table 3). Any common variance associated with task-general factors (such as motivation) would be expected to affect both measures similarly. By establishing a significant unique contribution of each predictor, we therefore established that general factors do not account for the relationship with change detection.

Detection sensitivity. In order to establish that the association between tasks could not be attributed to differences in response bias, the analyses were replicated using detection sensitivity (A; Zhang & Mueller, 2005). Change detection sensitivity was positively correlated with subitizing capacity, $r(278) = .37$, $p < .001$ (see Figure 3). In contrast, the detection decision criterion (b) was not correlated with subitizing capacity, $r(278) = -.08$, *ns*. These findings support the hypothesis that subitizing can predict visual perceptual capacity rather than response criterion. Again, there was also a positive correlation between change detection sensitivity and average estimation accuracy, $r(278) = .15$, $p = .013$ (see Figure 4), which was significantly weaker than the correlation between subitizing and detection sensitivity (difference z score $= -3.12$, $p = .002$).

Hierarchical regression was run, using subitizing capacity this time to predict change detection sensitivity, while controlling for estimation accuracy as before. Both steps of the regression were significant (Step 1: adjusted $R^2 = .02$, $p = .013$; Step 2: adjusted $R^2 = .19$, $p < .001$), and both subitizing capacity and estimation accuracy accounted for a significant portion of unique variance in the final model (as shown in Table 4), replicating the detection rate findings.

The results of Study 1 support the hypothesis that perceptual capacity as measured by subitizing can predict the rates of change detection or blindness. These results held when predicting either detection rates or detection sensitivity. Thus, increased capacity to subitize was associated with better ability to accurately detect changes and not simply an effect of response criterion. This relationship is unlikely to be explained simply by general factors such as motivation because subitizing accounted for a significant portion of unique variance when such factors were controlled by including estimation accuracy in multiple regression analyses. Larger number estimation is thought to reflect a different cognitive process to subitizing (e.g., Burr et al., 2010; Cutini, Scatturin, Moro & Zorzi, 2014; Vetter, Butterworth, & Bahrami, 2011) yet should have also been affected by general factors such as motivation. The finding of unique variance explained by subitizing capacity when estimation accuracy is controlled suggests that the perceptual capacity underlying subitizing is a specific predictor of change detection. The significant association between estimation accuracy and detection sensitivity was less expected. It is possible that the relationship may be related to some other cognitive process, to which Study 2 may provide insight.

Table 2
Correlation Matrix of Performance Measures for all Tasks in Study 1

Measure	1	2	3
1. Subitizing	—		
2. Estimation	.24** [.14, .34]	—	
3. Detection sensitivity (A)	.37** [.27, .48]	.15* [.06, .25]	—
4. Detection rate	.31** [.20, .42]	.15* [.04, .25]	.80** [.75, .84]

Note. Detection sensitivity and detection rate refer to performance on the change detection "flicker" task. Upper and lower 95% confidence intervals are presented in brackets.
* $p < .05$. ** $p < .005$.

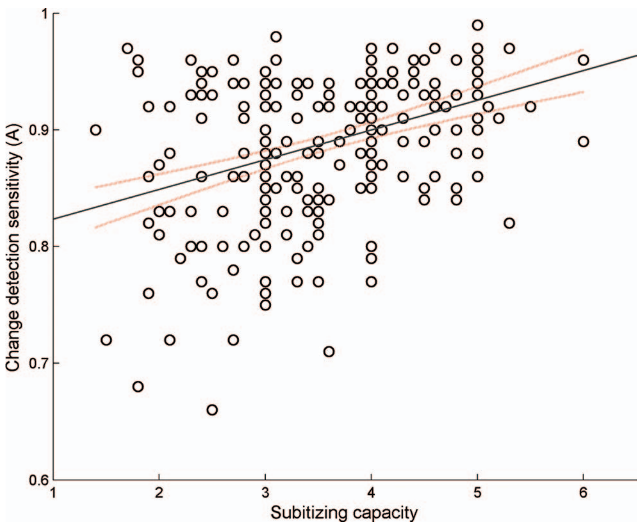

Figure 3. Change detection sensitivity and subitizing capacity correlation in Study 1. Dashed lines indicate 95% confidence intervals for the correlation. See the online article for the color version of this figure.

Study 2

Study 1 established that individuals with greater subitizing capacity were better able to detect changes in the flicker change detection paradigm, indicating a greater capacity for visual perception. In Study 2, we further investigated whether subitizing capacity is predictive of visual detection in a modified load-induced blindness task (Macdonald & Lavie, 2008). Participants performed a central task in which they made a line-length judgment of a centrally presented cross, the difficulty of which was established to be of an intermediate level of load in prior research (Remington et al., 2014). While performing the central task, participants attempted to detect the presence of a contrast increment in

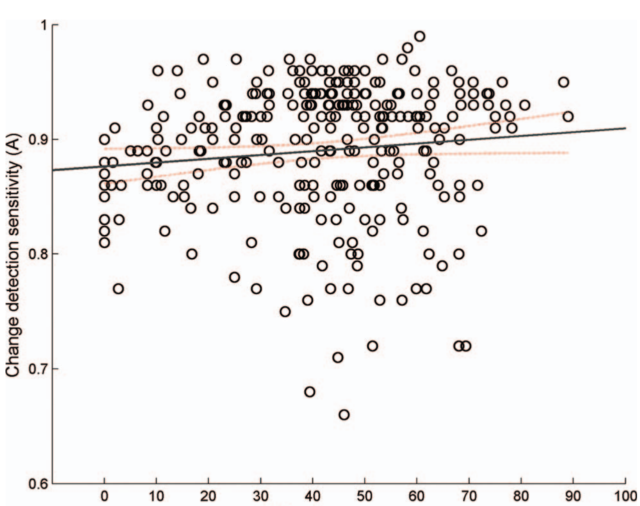

Figure 4. Change detection sensitivity and estimation accuracy correlation in Study 1. Dashed lines indicate 95% confidence intervals for the correlation. See the online article for the color version of this figure.

Table 4
Hierarchical Regression Predicting Change Detection Sensitivity From Subitizing (Step 2) While Controlling for Estimation Accuracy (Step 1)

Model	Predictor	β	*t*	*p*
Step 1	Constant		114.75	<.001
Adjusted $R^2 = .02$, $p = .013$	Estimation	.15	2.50	.013
Step 2	Constant		47.16	<.001
Adjusted $R^2 = .19$, $p < .001$	Estimation	.25	4.55	<.001
	Subitizing	.43	7.74	<.001

peripherally presented grating stimuli (see Figure 5). Our hypothesis of a generalized capacity for visual perception leads to the prediction that there should be a positive association between individuals' subitizing capacity and the ability to detect the presence of a contrast increment in the visual periphery.

Method

Participants. A total of 165 participants (80 male), aged 18 to 62 years ($M = 26.56$, $SD = 9.75$), completed Study 2. Participants' data were excluded from analysis if they performed at chance-level accuracy in the lowest set size of the enumeration task (10 participants), if their detection sensitivity was more than two standard deviations below the group average in the control block of the load-induced blindness task (13 participants), or if their accuracy in the central cross arm judgment was near chance in the main block of the load-induced blindness task (20 participants). The final sample analyzed was therefore 122 (59 male), aged 18 to 62 years ($M = 25.22$, $SD = 8.89$).

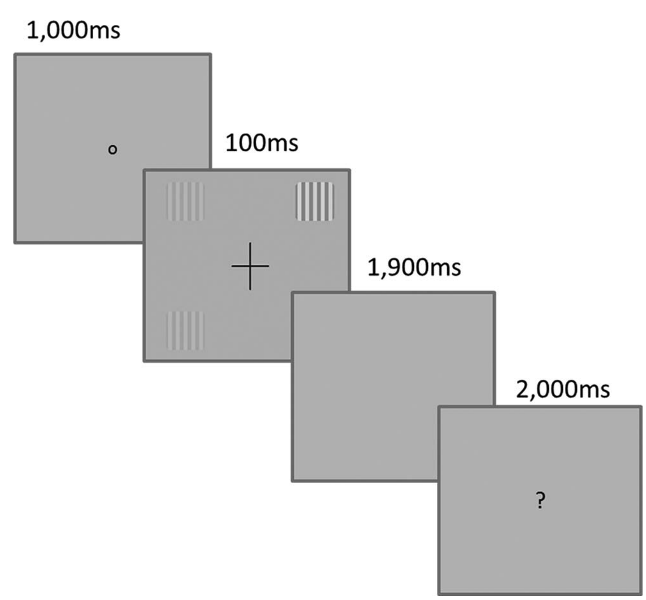

Figure 5. Example trial for the load-induced blindness task used in Study 2. Participants responded to the cross task during the first blank interval, and then upon the presentation of the question mark symbol, responded to the detection task.

As in Study 1, the sample size was dependent upon the number of museum visitors who were interested in taking part. Our sample of 122 provides a power greater than .99, assuming a similar effect size to that in Study 1 (i.e., Cohen's $f^2 = .21$ for a ΔR^2 of .17 when predicting change detection sensitivity).

Stimuli and procedure. The study was run in the museum's "Live Science" exhibition over a period of several consecutive weeks, which followed the run of Study 1. The study was run under the same conditions as Study 1, in groups of one to three, with at least one experimenter present at all times. The experimenters explained the tasks to the participants, and then initiated the study after obtaining written informed consent. Once again, volunteers received no payment for their participation. Participants completed the same visual enumeration task as described in Study 1. Instead of the change detection flicker task, this time, participants also completed a load-induced blindness task. The entire study took approximately 25 min to complete.

Each trial started with a central fixation dot presented for 1 s. This was followed by a central cross shape and four peripheral black-and-white square gratings for 120 ms. A blank screen was then presented for 1,880 ms, followed by a central "?" for 100 ms, and then another blank screen for a further 1,900 ms. The cross shape was formed of one vertical and one horizontal line, one of which was always longer (4.5 cm; 4.1° at a distance of 60 cm) than the other (3.5 cm; 3.3° at a distance of 60 cm). On a randomly selected 50% of trials, the vertical arm was longer; on other trials, the horizontal arm was longer. Each square grating was 3.6 cm × 3.6 cm (3.4° × 3.4° at a distance of 60 cm) and was presented in one of the four display corners 6.4 cm (6.1°) from the nearest grating edge to the center of the screen (extending to a maximum of 10.9° into the periphery). The contrast of the (nontarget) gratings was 10%; on 25% of trials, the contrast of one (target) grating was incremented by an additional 28%.

Participants were instructed to respond immediately after the stimulus presentation by pressing either the up-arrow key or the left-arrow key to indicate which cross arm (vertical or horizontal) was longer. A 1,900-ms blank interval followed the task presentation and this interval elapsed irrespective of the participant's response latency. A central question mark symbol "?" was then presented and participants were instructed to indicate whether the contrast increment was present in any of the four gratings by pressing the spacebar upon seeing this display.

The task included one practice block of 10 trials, followed by two experimental blocks of 32 trials, and, finally, one control block of 32 trials. The control block was identical to the experimental blocks except that participants were not required to attend to arm length discrimination. In the control block, the "?" prompt appeared immediately after the stimulus display, and participants were instructed to respond by indicating whether a contrast increment was present in one of the gratings. The control block was used to ensure visibility did not play a role in detection performance. Participants with a chance level of performance on this block were excluded from the main analysis, as described in the Participants section. Participants were instructed to maintain fixation throughout the task, as no one grating was more or less likely to be brighter than the others.

Results

Load-induced blindness task performance. Table 5 presents average performance in the contrast detection task for the entire sample. The same measures of detection sensitivity (A) and response criterion (b) as used in Study 1 were calculated for this data and used in subsequent analyses.

Enumeration task performance. As in Study 1, individual subitizing capacity was estimated by fitting a bilinear function to the individual accuracy data at each set size (excluding Set Size 9). Again, the bilinear function fit the data well (average RMSE = 8.10, SD = 4.40; average R^2 = .77, SD = .20). Average subitizing capacity was 3.32 (SD = 0.83), which again fits well with the typically observed limit of three to four items. Average estimation accuracy was 51.03% (SD = 11.01).

Detection rate. Table 6 presents a matrix of the correlations between performance measures of each of the tasks in Study 2. Subitizing capacity was positively correlated with detection rate in the load-induced blindness task, $r(121) = .29$, $p < .001$, as was estimation accuracy, $r(121) = .22$, $p = .014$, and these correlations were not significantly different (z = −0.65, p = .51).

As in Study 1, hierarchical regression was used to measure the unique contribution of each variable. The regression consisted of two steps: the first step included only estimation accuracy, and the second step included estimation accuracy followed by subitizing capacity. Both steps of the regression were significant (Step 1: adjusted $R^2 = .04$, $p = .014$; Step 2: adjusted $R^2 = .09$, $p = .008$). As can be seen in Table 7, subitizing capacity accounted for a significant portion of unique variance in the final model whereas estimation accuracy did not. As in Study 1, common variance associated with general factors such as motivation would be expected to affect both subitizing and estimation performance similarly. The finding that subitizing alone was a significant unique predictor of stimulus detection provides evidence against alternative accounts in terms of any general task performance factors.

Detection sensitivity. Detection sensitivity was positively correlated with subitizing capacity, $r(121) = .38$, $p < .001$ (see Figure 6). The detection decision criterion (b) was not significantly correlated, $r(121) = .08$, ns. Estimation accuracy was also correlated with detection sensitivity, $r(121) = .25$, $p = .006$ (see Figure 7), and although the correlation was numerically smaller than that with subitizing capacity, the two were not significantly different (difference z score = −1.25, p = .21).

Once again, a hierarchical regression was used to measure the unique contribution of each variable as in the analysis of detection rate. Both steps of the regression were significant (Step 1: adjusted $R^2 = .05$, $p = .006$; Step 2: adjusted $R^2 = .15$, $p < .001$). As can be seen in Table 8, subitizing capacity accounted for a significant

Table 5
Average Performance in the Load-Induced Blindness Task of Study 2

Measure	Mean	SD
Detection rate	.70	.21
False alarm rate	.24	.18
Detection sensitivity (A)	.80	.12
Response bias (b)	1.16	.55

Table 6
Correlation Matrix of Performance Measures for all Tasks in Study 2

Measure	1	2	3
1. Subitizing	—		
2. Estimation	.25** [.08, .44]	—	
3. Detection sensitivity (A)	.38** [.22, .52]	.25** [.08, .41]	—
4. Detection rate	.29** [.12, .43]	.22* [.05,.38]	.69** [.58, .78]

Note. Detection sensitivity and detection rate refer to performance on the load-induced blindness task. Upper and lower 95% confidence intervals are presented in brackets.
* $p < .05$. ** $p < .005$.

portion of unique variance in the final model, whereas estimation accuracy did not. As in Study 1, the finding that subitizing alone was a significant unique predictor of stimulus detection provides evidence against alternative accounts in terms of any general task performance factors such as motivation, as these would be expected to affect both subitizing and estimation performance similarly.

The results of Study 2 replicate the relationship between subitizing capacity and visual detection abilities established in Study 1. The positive association between these measures indicates a common underlying resource, one that cannot be attributed to general factors such as motivation, as demonstrated by the unique variance accounted for by subitizing. Although estimation accuracy in this study was positively correlated with stimulus detection, this correlation was not significant in a multiple regression including subitizing capacity, suggesting estimation accuracy alone was not a predictor of detection.

The dissociation between the correlation of estimation accuracy with detection sensitivity in change detection, but not load-induced blindness, tasks is potentially interesting. One may speculate that the association between large set size estimation and detection of changes in a meaningful visual scene is related to the ability to extract the "gist" (or summary statistic) of a visual display (e.g., Alvarez & Oliva, 2008). Outside of focused attention, the numerical gist of large quantities or the gist of a change versus no-change image may benefit from the same cognitive process. In contrast the local contrast increment detection required in the load-induced blindness task may depend on a more precise level of representation that can only be obtained within perceptual capacity, thus accounting for the selective correlation with subitizing capacity but not estimation of larger set sizes (see Ward, Bear, & Scholl, 2016, for a relevant discussion). As this is mere speculation at present and the focus of the present study was on subitizing rather than estimation, we do not dwell on this further.

Table 7
Hierarchical Regression Predicting Detection Rate in the Load-Induced Blindness Task From Subitizing Capacity (Step 2) While Controlling for Estimation Accuracy (Step 1)

Model	Predictor	β	*t*	*p*
Step 1	Constant		5.48	<.001
Adjusted $R^2 = .04$, $p = .014$	Estimation	.22	2.51	.014
Step 2	Constant		3.43	.001
Adjusted $R^2 = .09$, $p = .008$	Estimation	.16	1.75	.083
	Subitizing	.24	2.70	.008

Study 3

Studies 1 and 2 established subitizing as a predictor of visual detection in the change detection and load-induced blindness paradigms. In both studies, subitizing was a significant predictor when controlling for larger number estimation. This provides some evidence that an individual's subitizing capacity represents a distinct predictor of visual detection that is unlikely to reflect general cognitive factors or strategies, as these would apply to the estimation performance for larger numbers. In Study 3, we sought to further assess our hypothesis that subitizing capacity is reflective of a generalized perceptual capacity, as distinct from general cognitive ability, by specifically examining the relation to working memory capacity. Working memory is a well-established predictor of individual differences in a range of attention tasks, including, for example, the Stroop task, spatial cuing, and task switching (e.g., Kane, Bleckley, Conway, & Engle, 2001; Kane & Engle, 2000; Redick & Engle, 2006). However, as discussed earlier, in load theory, perceptual capacity and working memory capacity are two dissociable functions, and there are numerous demonstrations of opposite effects of working memory load and perceptual load on attention in support of this claim (see Lavie et al., 2004, for review). Thus, if subitizing reflects perceptual capacity, it should

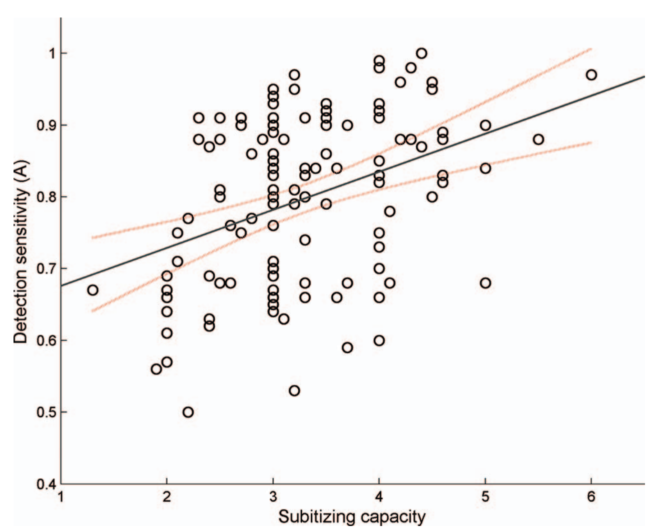

Figure 6. Detection sensitivity in the load-induced blindness task and subitizing capacity in Study 2. Dashed lines represent 95% confidence intervals for the correlation. See the online article for the color version of this figure.

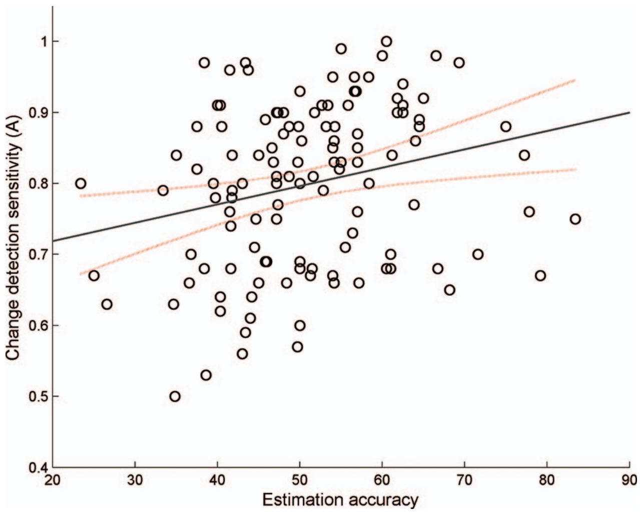

Figure 7. Detection sensitivity in the load-induced blindness task and estimation accuracy in Study 2. Dashed lines represent 95% confidence intervals for the correlation. See the online article for the color version of this figure.

remain a significant unique predictor of visual perception when controlling for individual differences in working memory capacity. In order to specifically address the cognitive control aspect of working memory, we chose three complex span tasks that involved not only memory retention but also load cognitive control in the form of multiple task demands. These have been reliably shown to predict performance of tasks requiring cognitive control of attention (e.g., Redick & Engle, 2006), and are thus predicted by load theory to be dissociable from perceptual capacity. In addition, recent research has demonstrated that using multiple versions of these tasks, which involve different stimulus categories (such as numerical, spatial, and verbal memoranda), can produce measures more sensitive to domain-general working memory functions than when using only a single task (e.g., Foster et al., 2015; Oswald, McAbee, Redick, & Hambrick, 2015).

Furthermore, in Studies 1 and 2, the enumeration task and both visual detection tasks required detection of briefly presented (less than a quarter of a second) or transient stimuli. It is plausible that the common variance is restricted to the capacity for perception from rapid, transient presentations rather than perceptual capacity in a wider sense, which extends to longer and more continuous presentations. To test this in Study 3, we included a continuous measure of perceptual capacity (MOT), which does not involve rapid or transient displays. In Study 3, we thus assessed individual differences in working memory capacity, subitizing, transient change detection in the flicker task (as used in Study 1), and continuous perception of moving objects with the MOT task.

Method

Participants. Seventy-two (43 female) participants, aged 18 to 52 years ($M = 24.42$, $SD = 6.99$), were recruited from the University College London (UCL) psychology research volunteer database, and each received £7.50 (approximately $10.50) for their time. All participants provided written informed consent prior to taking part. As in Study 1, participants were excluded if their accuracy was near chance for the lowest set size of the enumeration task, leading to the exclusion of four participants (three male) and a final sample size of 68. Assuming a similar effect size as Studies 1 and 2 (i.e., Cohen's $f^2 = .21$; see Study 2), the sample of 68 provided a power of .96 to detect a change in R^2 in a regression controlling for estimation accuracy and three measures of working memory capacity (see Procedure).

Procedure. Study 3 was run at UCL, in a quiet testing room, and volunteers participated one at a time. Participants completed a total of five tasks: three complex span working memory tasks, an enumeration task, an object tracking task (MOT), and a change detection flicker task. There was always a researcher present in the room with the participants during the study. The study took approximately 1 hr.

Enumeration task. Participants completed the same enumeration task as in Studies 1 and 2, except for the following changes: The length of each block was increased to 81 trials, and a fourth experimental block was added to the task (producing a total of 324 trials).

Change detection task. Participants completed the same change detection task as used in Study 1; however, this time the task included eight additional trials (total = 52 trials). The task structure was the same except that the flickering presentation time was reduced to 8 s.

MOT task. Participants completed a MOT task in which they were required to track four target dots as they moved around the center of the screen among four nontarget dots (see Figure 8). The dots subtended 0.5 cm × 0.5 cm (0.5° at a distance of 60 cm) and moved randomly within an area subtending 6 cm × 6 cm (5.72° at a distance of 60 cm) at the center of the screen. On each trial, eight black dots were presented against a gray background; after 500 ms, four of the dots became blue for 1.5 s, after which they returned to being black. After another 500 ms, the dots began to move at a rate of 2.15°/s; the dots bounced off one another and off the edges of the movement area. After 8 s, the dots ceased movement and a single probe dot became blue once more. Participants responded to the probe by pressing the "1" key on the keyboard number pad if the probe was a target, and the "2" key, if not. The probe then turned either green or red to indicate a correct or incorrect response, respectively. A fixation cross was then presented for 1 s before the next trial started.

Complex span tasks. Participants completed three complex span working memory tasks: the operation span (OSPAN) task, the reading span (RSPAN) task and the symmetry span (SSPAN) task (the same as those described in Oswald et al., 2015). These

Table 8
Hierarchical Regression Predicting Detection Sensitivity in the Load-Induced Blindness Task From Subitizing Capacity (Step 2) While Controlling for Estimation Accuracy (Step 1)

Model	Predictor	β	*t*	*p*
Step 1	Constant		13.71	<.001
Adjusted $R^2 = .05$, $p = .006$	Estimation	.25	2.77	.006
Step 2	Constant		10.43	<.001
Adjusted $R^2 = .15$, $p < .001$	Estimation	.16	1.77	.080
	Subitizing	.34	3.89	<.001

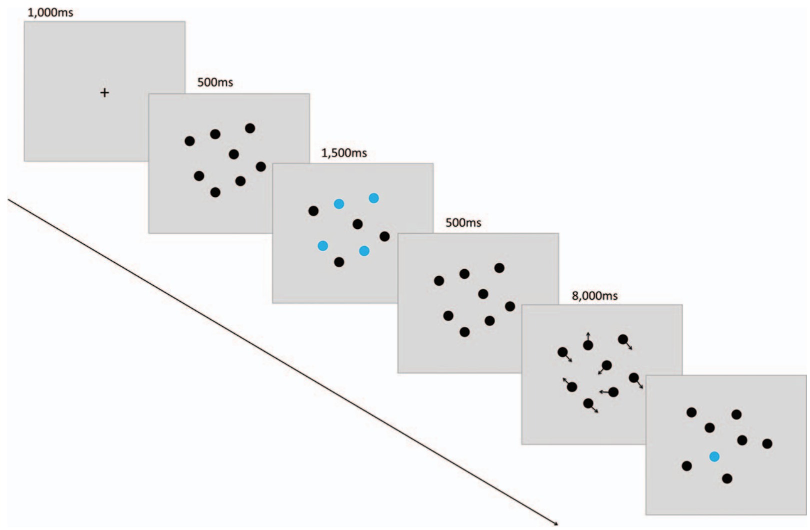

Figure 8. The Multiple Object Tracking task used in Study 3. Participants were presented with eight black dots, four of which briefly turned blue before turning back to black; all eight dots then moved around randomly for 8 s. The dots then stopped moving, one turned blue again, and the participant responded by indicating whether or not this was one of the original targets. See the online article for the color version of this figure.

shortened versions of the tasks provide the opportunity for a more representative measure of working memory, nonspecific to a particular cognitive modality (numerical, lexical, or spatial). Using a variety of shortened working memory span tasks in lieu of a single full-length task has been shown to provide a better measure of underlying capacity (see Foster et al., 2015, and Oswald et al., 2015, for an in-depth discussion).

E-Prime 2.0 was used to run these tasks. The task procedure was similar for all three tasks. In the OSPAN task (see Figure 9), participants were presented with a series of sums (e.g., [8/2] + 9 = 13). They responded to each sum by clicking "yes" or "no" icons on the screen to indicate whether the given answer was correct. Following each sum, participants were presented with a letter, which they memorized. After a variable number of sum and letter presentations (range from 4–6), the participant was presented with a memory response screen, from which they selected the memorized letters in the order in which they were presented. If they were uncertain of a given memoranda, they responded with "blank." The number of letters recalled in the correct sequential position over the course of the task provided the participant's "span" score.

Before starting the task, the participants completed a series of practice trials, first performing only the "sum" component with no memoranda, and then only the "memory" component with no sums, and, finally, both together, as in the experimental trials. The average RT from the final practice section plus two standard deviations was used as the time limit in experimental trials. Throughout the task, the participant's accuracy (% correct) in the operation portion of the task was displayed, and they were instructed to maintain a minimum of 80% accuracy.

The RSPAN task followed the same task structure; however, instead of a sum on each trial, the participant read a sentence and responded to indicate whether or not the sentence made sense (e.g., "The prosecutor's dish was lost because it was not based on fact"). The SSPAN task followed the same structure, but instead of a sum or sentence, the participant responded to a black-and-white block image, indicating whether or not the left and right sides were mirror-symmetrical. In the SSPAN task, instead of memorizing letters, the participant memorized the position of a black square in a white grid.

Results

Enumeration task performance. A bilinear function was fitted to the individual accuracy data at each set size (excluding set size nine), as before, in order to estimate individual subitizing capacity. Again, the bilinear function fit the data well. The same curve-fitting procedure was used as in Studies 1 and 2 to estimate individual subitizing capacity. The average RMSE for the fit was 8.26 (SD = 4.75) and average adjusted R^2 was .76 (SD = .22), indicating a good fit of the model to the data. As previously, a subitizing range was estimated for each participant based on the point at which the two linear components of the bilinear function intersected. Average subitizing capacity was 3.17 (SD = 0.84), which is within range of our previous findings using this task. Accuracy at set sizes beyond the subitizing range was averaged as a measure of "estimation" ability; average estimation accuracy was 49.10 (SD = 14.35), which was also within the range found earlier.

Change detection task performance. Table 9 presents average performance for the change detection task in Study 3; once again, false alarm rates were very low, so the nonparametric measure of detection sensitivity (A) was calculated with the corresponding measure of bias.

MOT task performance. Average accuracy in the MOT task was well above chance (mean accuracy = 75.19%, SD = 12.76). In order to obtain an estimate of tracking capacity comparable with the subitizing capacity estimate, we calculated the effective number of objects tracked (ENOT) using the formula described by Scholl, Pylyshyn, and Feldman (2001). ENOT scores are calcu-

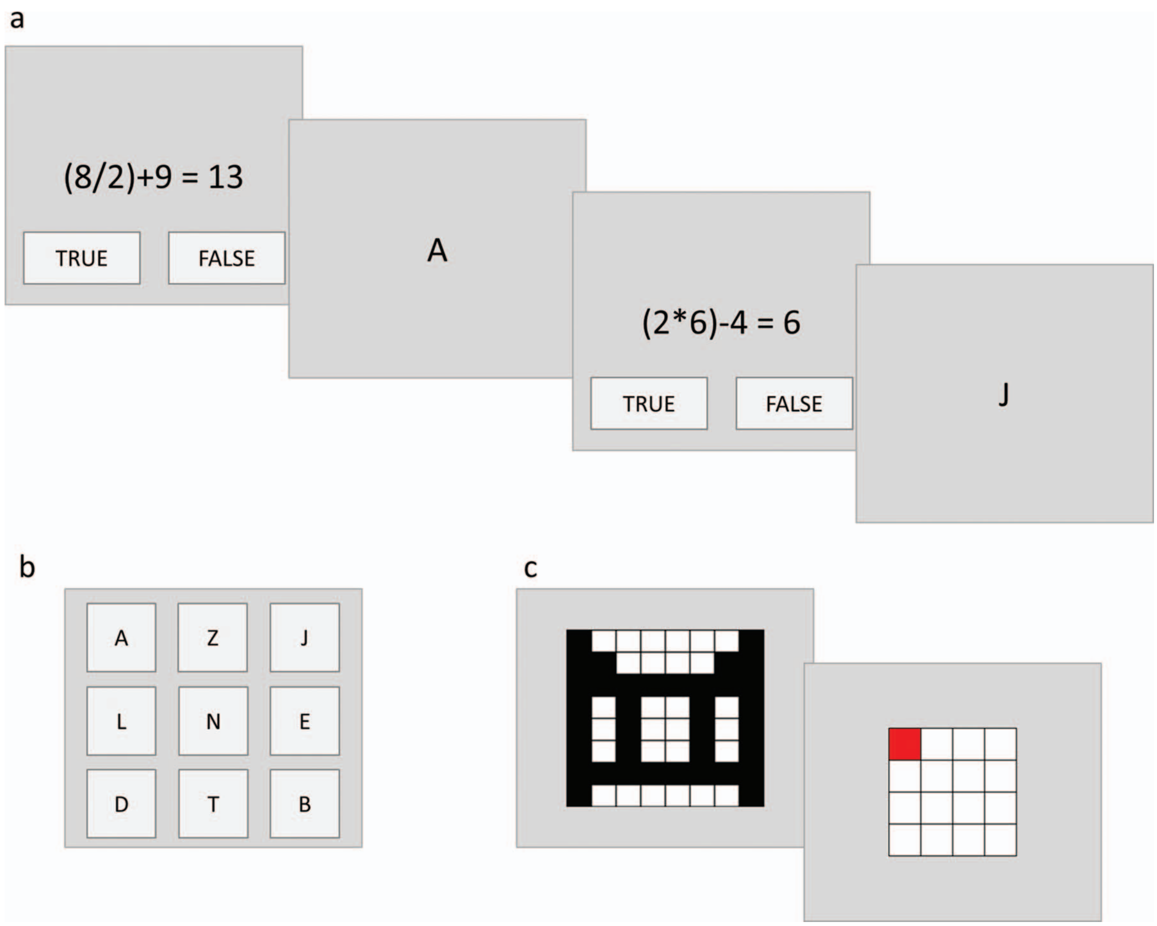

Figure 9. (a) A typical trial in the Operation span task. Participants perform a series of sums and memorize subsequently displayed letters. (b) After a variable number of trials a memory test screen is presented. (c) In the Symmetry span task, symmetry judgments take the place of sums and location probes take the place of letter memoranda. See the online article for the color version of this figure.

lated as $m = n\,(2p - 1)$, where m is the estimated tracking capacity (ENOT), n is the number of tracking targets, and p is the proportion of correct responses. The average capacity based on this formula was 1.90 (SD = 0.84).

Complex span task performance. Table 10 presents average performance data for each of the complex span tasks. The total score on each task was used, as this has previously been established as the better measure of individual capacity (Redick et al., 2012). The total score is calculated as the total number of memoranda (letters or square positions) reported in the correct position in sequence (ignoring incorrect or unknown items). The SSPAN score is necessarily lower, as there were fewer overall trials in this task. The maximum possible scores are 30 for the OSPAN and RSPAN tasks, and 24 for the SSPAN task. As can be seen from Table 10, average accuracy on the "operation" portion of the tasks was very high: No participant scored below 80% (the recommended cutoff to ensure that participants are performing both parts of the task).

Predicting change detection from subitizing capacity. We first examined whether perceptual capacity as measured by subitizing significantly predicted change detection rates when controlling for working memory capacity using hierarchical regression.

Table 9
Average Performance in the Change Detection Task of Study 3

Measure	Mean	*SD*
Detection rate	.50	.12
False alarm rate	.01	.09
Detection sensitivity (A)	.82	.08
Bias (b)	2.41	.69

Table 10
Average Span Score and Operation Accuracy in Each of the Complex Span Tasks

Task	Mean score (*SD*)	Mean accuracy (*SD*)
OSPAN	25.27 (5.34)	96.74 (3.48)
RSPAN	23.50 (4.51)	95.81 (3.90)
SSPAN	18.09 (4.62)	98.04 (2.65)

Note. OSPAN = Operation span; RSPAN = Reading span; SSPAN = Symmetry span.

The first step included only the working memory span scores; subitizing range and estimation accuracy were added in the second step. The full regression is presented in Table 9. The first step of the regression including all the working memory span tasks did not significantly predict change detection (adjusted $R^2 = -.03$, *ns*). The second step was significant (adjusted $R^2 = .18$, $p < .001$), as predicted. As can be seen in Table 11, subitizing capacity and estimation accuracy were both significant predictors of change detection rates when controlling for working memory.

These results were fully replicated when the same analyses were run using detection sensitivity (A). The stepwise regression showed that subitizing significantly predicted detection sensitivity ($\beta = .29$, $t = 2.26$, $p = .027$), while controlling for working memory. In addition, as in Study 1, there was no relationship between response bias (b) in the change detection task and either subitizing, $r(68) = -.05$, *ns*, or estimation accuracy, $r(68) = -.14$, *ns*.

Thus, in replication of Study 1, both subitizing capacity and estimation accuracy appeared to measure distinct constructs, both of which are predictive of change detection performance. Study 3 further showed that this prediction cannot be explained by working memory or other general task-taking aptitudes, as the prediction remains significant when controlling for complex span working memory capacity.

Predicting MOT from subitizing capacity. Next, we examined whether subitizing capacity could predict a more continuous measure of perceptual capacity, as reflected in the MOT task, while controlling for any shared variance with working memory capacity. We thus used a multiple regression, in which the first step included working memory capacity as a control variable, and the second step included subitizing and estimation accuracy, as in previous analyses. The full regression is presented in Table 12. The first step of the regression was significant (adjusted $R^2 = .09$, $p = .029$). More importantly the second step was also significant (adjusted $R^2 = .22$, $p = .004$), indicating common variance between subitizing and MOT capacity separate from any variance associated with working memory capacity (see Figure 10), as predicted from our general perceptual capacity hypothesis and in line with load theory.

Taken together, the findings that subitizing predicted both change detection and MOT independently of working memory supports the hypothesized perceptual capacity as the construct underlying common variance between subitizing and visual perception tasks. Moreover, the differences in the transient versus continuous nature of change blindness and MOT, respectively, supports further the notion that their covariance with subitizing reflects individual differences in a more generalized perceptual capacity.

Testing the generalized perceptual capacity hypothesis. The perceptual capacity hypothesis predicts that individual differences in MOT, change detection, and subitizing all depend upon the same underlying capacity, which is distinct from working memory capacity. To further examine this hypothesis, it is necessary to establish the relationship between MOT and change detection. This relationship should not be attributable to working memory capacity but rather to perceptual capacity, as previously measured with subitizing. Therefore, MOT capacity should predict change de-

Table 11
Hierarchical Regression Predicting Change Detection From Complex Span Working Memory Capacity (Step 1), Subitizing, and Estimation Accuracy (Step 2)

Model	Variable	β	*t*	*p*
Step 1	Constant		4.585	<.001
Adjusted $R^2 = -.03$, *ns*	OSPAN	−.032	−.224	.823
	RSPAN	.059	.424	.673
	SSPAN	.108	.806	.423
Step 2	Constant		2.641	.010
Adjusted $R^2 = .18$, $p < .001$	OSPAN	.028	.206	.837
	RSPAN	−.126	−.950	.346
	SSPAN	−.006	−.048	.962
	Estimation	.310	2.469	.016
	Subitizing	.390	3.270	.002

Note. OSPAN = Operation span; RSPAN = Reading span; SSPAN = Symmetry span; *ns* = not statistically significant.

Table 12
Hierarchical Regression Predicting MOT Capacity From Working Memory Capacity (Step 1), Subitizing, and Estimation Accuracy (Step 2)

Model	Variable	β	*t*	*p*
Step 1	Constant		.085	.933
Adjusted $R^2 = .09$, $p = .029$	OSPAN	.134	.996	.323
	RSPAN	.187	1.429	.158
	SSPAN	.156	1.240	.219
Step 2	Constant		–1.559	.124
Adjusted $R^2 = .22$, $p = .004$	OSPAN	.210	1.599	.115
	RSPAN	.032	.247	.806
	SSPAN	.090	.732	.467
	Estimation	.160	1.303	.198
	Subitizing	.361	3.088	.003

Note. MOT = Multiple object tracking capacity; OSPAN = Operation span; RSPAN = Reading span; SSPAN = Symmetry span.

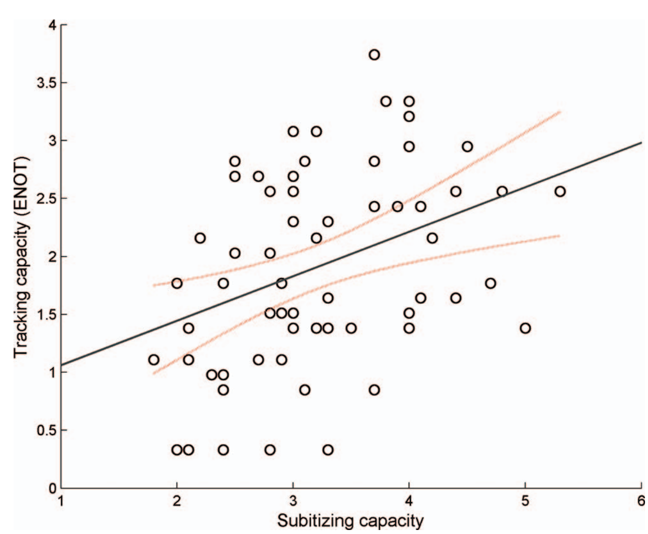

Figure 10. Object tracking capacity (Effective number of objects tracked) and subitizing capacity correlation in Study 3. Dashed lines represent 95% confidence intervals for the correlation. See the online article for the color version of this figure.

tection performance when controlling for working memory span but not when controlling for subitizing.

To test this hypothesis, we first ran a regression that included the working memory span scores and estimation accuracy in its first step (thus controlling for executive working memory capacity and general cognitive factors involved in estimation but not perceptual capacity), and both working memory and tracking capacity (ENOT) in the second step. The findings (see Table 13) show that MOT significantly predicted change detection (adjusted $R^2 = .10$, $p = .04$; see (see Figure 11) when working memory was controlled in support of our first prediction.

A further regression (see Table 14) was run to test the second prediction that subitizing (rather than working memory) accounts for the common variance between MOT and change detection. This regression included working memory span measures, estimation accuracy, and subitizing capacity as control variables in its first step, and MOT capacity in the second step. The first step was significant (adjusted $R^2 = .18$, $p = .003$), indicating that subitizing and estimation significantly predicted change blindness, as before, whereas the second step was not significant (adjusted $R^2 = .18$, *ns*), indicating that MOT does not contribute unique variance to the prediction of change detection when controlling for subitizing, in line with our hypothesis.

Thus, MOT capacity appears to significantly predict change detection when controlling for variance accounted for by working memory capacity, paralleling the profile observed with perceptual capacity for subitizing. Taken together, the results indicate that a single underlying construct appears to underlie subitizing, change detection, and MOT, and this construct is distinct from working memory capacity. This is in accordance with our prediction of a general perceptual capacity as distinct from the capacity for cognitive control (as stipulated in load theory, e.g., Lavie et al., 2004).

Reliability of measures. The far larger number of trials in the enumeration task in Study 3 afforded a reliability analysis based on split-half correlations.[2] The data for each task was split such that every other trial throughout the task was assigned to one split or the other, respectively. Spearman-Brown-corrected correlation coefficients are presented in Table 15. As shown in the table, positive correlations between the split halves were significant for each of

Table 13
Hierarchical Regression Predicting Change Detection Rate From Working Memory Capacity and Estimation Accuracy (Step 1), Followed by MOT Capacity (Step 2)

Model	Variable	β	*t*	*p*
Step 1	Constant		4.382	<.001
Adjusted $R^2 = .06$, *ns*	OSPAN	−.090	−.651	.518
	RSPAN	.015	.113	.910
	SSPAN	−.002	−.011	.991
	Estimation	.352	2.628	.011
Step 2	Constant		4.518	<.001
Adjusted $R^2 = .10$, $p = .041$	OSPAN	−.116	−.852	.398
	RSPAN	−.026	−.196	.845
	SSPAN	−.025	−.193	.848
	Estimation	.301	2.262	.027
	MOT	.254	2.007	.041

Note. MOT = Multiple Object Tracking capacity; OSPAN = Operation span; RSPAN = Reading span; SSPAN = Symmetry span; *ns* = not statistically significant.

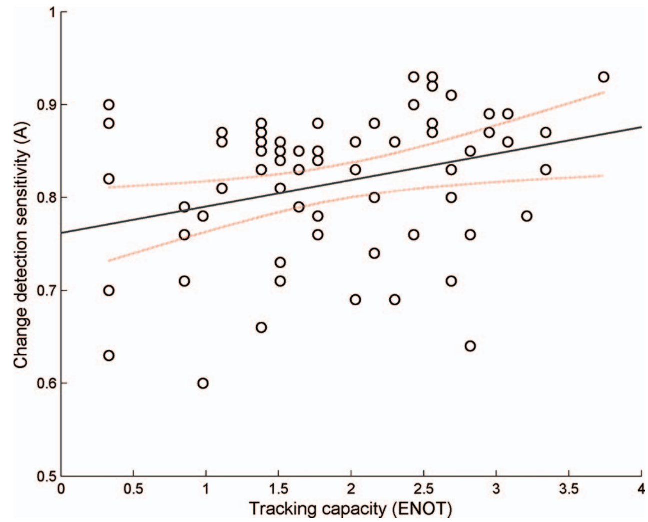

Figure 11. Object tracking capacity (Effective number of objects tracked) and change detection rate correlation in Study 3. Dashed lines represent 95% confidence intervals for the correlation. See the online article for the color version of this figure.

the measures. Importantly, the reliability of estimation accuracy ($r = .89$) was higher than that of subitizing capacity ($r = .70$). Thus, clearly, the unique relationship between subitizing and the other perceptual measures is not attributed to greater reliability of the subitizing measure compared with the estimation measure.

Factor Analysis

Principle components analysis. The results reported thus far suggest that there are two distinct constructs underlying performance across the tasks—one representing perceptual capacity and another representing working memory capacity. To examine this possibility further, we applied a factor analysis approach to the data.

Behavioral performance scores for each of the variables of interest (subitizing, change detection sensitivity, MOT, OSPAN, RSPAN, and SSPAN scores) were first entered into a principle components analysis (PCA) with an orthogonal (varimax) factor rotation. The Keyser-Meyer-Olkin (KMO) measure of sampling adequacy indicated that the sample was adequate (KMO = .59; Field, 2009; Kaiser, 1970). Bartlett's test for sphericity was significant, $\chi^2(15) = 60.02$, $p < .001$, suggesting that there were sufficient interitem correlations for PCA.

Principle components were extracted with eigenvalues greater than 1 (Kaiser, 1974). This resulted in a two-factor solution, and was also supported by examination of a scree plot in which there was a clear point of inflection at the third factor. The first factor accounted for 35.25% of the overall variance and the second factor accounted for 22.44% (57.69% cumulatively).

The rotated factor loadings for each variable are presented in Table 16 and Figure 12. As can be seen from the table, the first

[2] For the enumeration task in Studies 1 and 2, there were an insufficient number of trials to effectively fit the bilinear function with only half of the data.

Table 14
Hierarchical Regression Predicting Change Detection Rate From Working Memory Capacity, Estimation Accuracy, and Subitizing (Step 1), Followed by MOT Capacity (Step 2)

Model	Variable	β	*t*	*p*
Step 1	Constant		2.641	.010
Adjusted R^2 = .18, p = .003	OSPAN	.028	.206	.837
	RSPAN	−.126	−.950	.346
	SSPAN	−.006	−.048	.962
	Estimation	.310	2.469	.016
	Subitizing	.390	3.270	.002
Step 2	Constant		2.779	.007
Adjusted R^2 = .18, *ns*	OSPAN	.001	.007	.994
	RSPAN	−.130	−.980	.331
	SSPAN	−.017	−.138	.890
	Estimation	.289	2.275	.026
	Subitizing	.344	2.686	.009
	MOT	.127	.979	.332

Note. MOT = Multiple Object Tracking capacity; OSPAN = Operation span; RSPAN = Reading span; SSPAN = Symmetry span; *ns* = not statistically significant .

component is indicated by working memory variables, all of which have high, positive loadings. Conversely, the second factor is indicated by the "perceptual" variables, which have similarly high and positive loadings. The results of this analysis therefore support the conclusion that two distinct and dissociable factors underlie working memory and perceptual capacity, respectively. Interestingly, MOT appears to not just load on the perceptual component but also to moderately load on the first component of working memory. Thus, in addition to perceptual resources, MOT appears to also involve some working memory capacity.

Confirmatory factor analysis. As a further test of the hypothesis that two distinct factors underlie performance across the tasks, we replicated the model provided by the PCA in a confirmatory factor analysis. This allowed us to formally compare the best-fitting model provided by the PCA with other possible models, providing a better insight into the nature of the latent structure of the data. This and other models were assessed using LISREL 8 (Scientific Software International, Inc., Chicago, IL) using a maximum likelihood estimation procedure based on the correlation matrix presented in Table 17.

Table 15
Split-Half Correlations for Each Task

Measure	Spearman-Brown corrected correlation coefficient
Change detection (Study 1)	.69
Change detection (Study 3)	.72
Load-induced blindness	.67
Subitizing	.70
Estimation	.89
MOT	.87
OSPAN	.95
RSPAN	.84
SSPAN	.91

Note. All correlations were significant and positive ($p < .001$ for all). MOT = Multiple Object Tracking capacity; OSPAN = Operation span; RSPAN = Reading span; SSPAN = Symmetry span.

Table 16
Varimax Rotated Factor Loadings of Each Behavioral Variable on Both Factors Produced by the Principle Components Analysis

Measure	Component 1 loading	Component 2 loading
OSPAN	.83	−.09
RSPAN	.70	.23
SSPAN	.69	.05
Subitizing	−.01	.81
Change detection (A)	−.01	.69
MOT	.42	.65

Note. OSPAN = Operation span; RSPAN = Reading span; SSPAN = Symmetry span; MOT = Multiple Object Tracking capacity.

First, we tested the null hypothesis of an independence model (with no structure) and established that it was significantly different to the observed date, $\chi^2(15) = 67.517$, $p < .001$; thus, a model with no structure does not fit the data well.

We then tested our hypothesized model, which included two latent variables: One representing working memory, indicated by the three complex span tasks; the other representing perceptual capacity, indicated by subitizing, MOT, and change detection sensitivity. In line with the PCA results, MOT was also allowed to cross-load on both latent factors.

This model fit the data well; the minimum fit function chi-square test of difference to the observed data was nonsignificant, $\chi^2(8) = 10.83$, $p = .21$, indicating that the model does not significantly differ from the observed data. The standardized root mean residual for the hypothesized model was .07, indicating a good fit (for which .08 or lower residual variance is required; Tabachnick & Fidell, 2013). The Akaike information criterion (AIC) was 35.96, lower than both the independence and saturated models (79.52 and 42.0, respectively), suggesting that the fit was

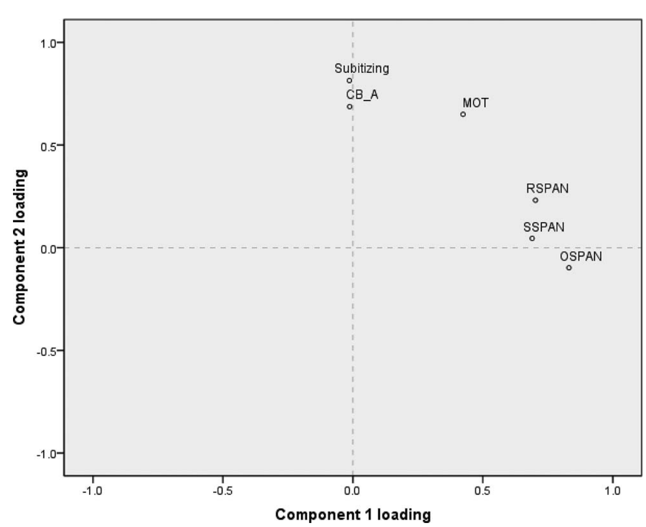

Figure 12. Factor loadings of each variable: subitizing capacity (Subitizing), change detection sensitivity (CB_A) Tracking capacity (MOT), Reading span (RSPAN), Symmetry span (SSPAN) and Operation span (OSPAN) in varimax-rotated space. Note that dashed lines represent a loading of zero on each component axis.

Table 17
Correlation Matrix of Performance Measures for all Tasks in Study 3

Measure	1	2	3	4	5	6	7
1. Subitizing	—						
2. Estimation	.12 [−.11, .35]	—					
3. Detection sensitivity (A)	.27* [.07, .45]	.19 [−.09, .42]	—				
4. Detection rate	.39** [.17, .57]	.33* [.08, .53]	.57** [.40, .73]	—			
5. MOT (ENOT)	.37** [.18, .53]	.32* [.13, .50]	.30* [.07, .51]	.30* [.09, .50]	—		
6. OSPAN	−.11 [.40, .20]	.33* [.12, .50]	.06 [−.24, .33]	.03 [−.18, .20]	.27* [.07, .46]	—	
7. RSPAN	.26* [.04, .48]	.29* [.09, .47]	.04 [−.23, .30]	.08 [−.16, .29]	.29* [.06, .49]	.44** [.20, .60]	—
8. SSPAN	.05 [−.20, .31]	.40** [.21, .57]	.06 [−.15, .27]	.11 [−.12, .32]	.26* [.04, .45]	.35** [.11, .56]	.28** [.09, .47]

Note. Detection sensitivity and detection rate refer to performance on the change detection "flicker" task. Upper and lower 95% confidence intervals are presented in brackets. MOT = Multiple Object Tracking capacity; ENOT = Effective Number of Objects Tracked; OSPAN = Operation span; RSPAN = Reading span; SSPAN = Symmetry span.
* $p < .05$. ** $p < .005$.

superior to these alternative models, with either no relationships or with unstructured relationships between every variable. The comparative fit index was .95, also indicating a good fit (Tabachnick & Fidell, 2013). Figure 13 represents the standardized factor loadings for the hypothesized model. All of the estimated factor loadings were significant ($p < .05$ for all). As can be seen in Figure 13, the loading of MOT on the perceptual variable was numerically larger than that on the working memory variable; however, both loadings were statistically significant.

Finally, we also tested a model representing the alternative hypothesis that all of the variance observed in the data may be best described by a single latent factor. The fit of this model was also poor and was rejected on the basis of a significant minimum fit function chi-square test, $\chi^2(9) = 25.07$, $p = .003$. The AIC was 49.06, also higher than our hypothesized model demonstrating more unexplained variance.

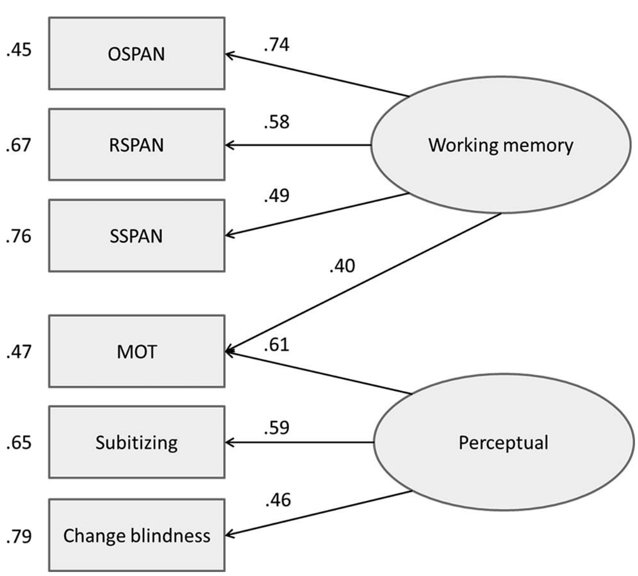

Figure 13. Confirmatory factor analysis results. Residuals (shown on the left of the variables) and factor loadings are based on the "completely standardized solution" from LISREL 8.

General Discussion

The present findings establish a common perceptual capacity limit for visual detection, as measured in four different tasks: subitizing, MOT, load-induced blindness, and in a change detection task often referred to as *change blindness*. Specifically, the findings show that an individual who is able to subitize a larger number of items from a brief display will have better accuracy and sensitivity for detection of changes in meaningful scenes (in the change detection task) as well as for detection of peripheral stimuli while attention is occupied in a central task (in the load-induced blindness paradigm).

Moreover, although subitizing necessitates rapid encoding from brief displays, the MOT task used in Study 3 involved continual tracking for several seconds and appears to rely upon the same underlying capacity. The results of Study 3 thus establish that the observed individual differences in perceptual capacity are common to continual deployment of attention to nontransient displays in the MOT task. Importantly, the results showed that subitizing capacity was consistently either a distinct factor alongside estimation ability, or the only unique factor after estimation ability was controlled for in multiple regression analyses. These results provide evidence against general factors explaining the effect (e.g., motivation), because these would be reflected in the common variance in task performance both within and beyond the subitizing range.

In Study 3, in addition to the estimation accuracy, we also explicitly controlled for working memory capacity using complex span tasks involving a variety of cognitive modalities. These tasks are specifically designed to measure working memory capacity in the face of distracting dual-task goals that load cognitive control resources. Complex span tasks have repeatedly been demonstrated as powerful predictors of various aspects of cognitive performance, including the control of attention (e.g., Redick & Engle, 2006) and general fluid intelligence (Foster et al., 2015; Redick et al., 2012; Unsworth, Redick, Heitz, Broadway, & Engle, 2009). Furthermore, the influence of any particular domain-specific memory function was reduced by measuring the common variance between multiple tasks involving a variety of stimulus classes. Perceptual capacity, as measured by subitizing (and object tracking) capacity, was still a strong predictor of change detection when controlling for working memory capacity across these varied measures of working memory span.

Overall, then, the present results cannot be explained by a specific capacity for stimulus detection under transient, very brief presentations (because they extend to continuous tracking), nor can they be explained by a general cognitive ability or working memory capacity. Instead, these findings support a construct of perceptual capacity underlying common variance between subitizing and visual perception tasks. The confirmatory factor analyses in Study 3 further supported this conclusion, showing that the best-fitting model was one that included two latent factors, which represented distinct perceptual capacity and working memory capacity. An alternative model that only included one "general" latent factor did not fit the data well, supporting the hypothesis that subitizing and the change detection and MOT tasks depend upon a distinct underlying attentional capacity for perceptual processing. Interestingly, in the best-fitting model, the capacity for tracking multiple moving objects loaded not only on the perceptual factor but also, to a smaller extent, on working memory. This is perhaps to be expected given that only the MOT task involved extended durations (8-s trial) and required active maintenance of each target object, despite the continuous change of each object positions throughout the full trial duration.

Of course, each of the tasks used involved other specific sources of variance—for example, the ability to divide spatial attention between fixation and the periphery (in the load induced blindness task), a search (for a change) component (in the change detection task), and perceptual grouping factors across motion (in the MOT task) or static stimuli (in the subitizing task), to name but a few. Such factors should account for some of the variance not explained by generalized perceptual capacity to perceive more items in parallel (e.g., irrespective of whether these are grouped or ungrouped). Despite the possible contribution of various different cognitive resources to task performance, the present results indicate that the perceptual capacity of attention is consistently a factor in tasks involving perceptual load. This therefore supports the importance of perceptual capacity as a key component of attentional processing across various task demands.

A common perceptual capacity limit of attention in tasks involving high perceptual load is consistent with previous studies of the load theory of attention. Previous research has provided support for a general capacity limit by demonstrating that various manipulations of load (e.g., feature vs. conjunction discrimination in nonspatial search, increased set size in spatial search, object perception across rotation) converge upon the same result: reduced perception of stimuli outside the focus of attention. Here, we find novel support from an individual differences perspective by establishing that an individual's capacity limits are correlated across different visual perception tasks and are distinct from capacity for higher level cognitive control.

The diversity of the tasks examined here further attests to the generality of perceptual capacity limits. In the subitizing task, numerical judgments were made based on a single, brief display of simple, square stimuli, whereas in the change detection task, the visual display flickered repeatedly for several seconds, requiring a search among relatively complex real-world scenes; in the load-induced blindness task, a line-length discrimination task was combined with contrast increment detection in the periphery; and, finally, the MOT task involved a continuous display with minimal requirement for rapid encoding. Despite these differences, these tasks all recruit a common perceptual capacity.

The present results are consistent with a growing body of literature demonstrating that subitizing depends upon the allocation of attention, so that subitizing capacity is reduced when subjects pay attention to another task, especially under conditions of high perceptual load (e.g., Vetter et al., 2008, 2011, and others; see the general introduction for review). Indeed, the findings of a direct relation between subitizing capacity and the number of objects tracked in a motion tracking task (Chesney & Haladjian, 2011, and the present work) is highly suggestive of common perceptual capacity across tasks. Our findings complement this previous work in demonstrating common intraindividual perceptual capacity across subitizing, MOT, and visual detection tasks, while also controlling for nonperceptual variables. We also note a recent finding that the subitizing phenomenon typically assessed with simple shapes generalizes also to real-world stimuli (Railo, Karhu, Mast, Pesonen, & Koivisto, 2016). This is consistent with our demonstration that the capacity underlying subitizing generalizes to visual detection for both meaningful real-world stimuli and more elementary, simple shapes.

Our results establish the subitizing task as a simple quantification of an individual's general perceptual capacity limit that can predict their performance in visual detection tasks, and object tracking as a parallel measure of the same capacity for perception. As such, they provide a potentially powerful indicator of individual abilities relevant to various tasks in industry, defense, and security. Many roles depend on an individual's visual detection and object tracking capacity, for example, x-ray screening and CCTV monitoring. The present research thus provides a scientific basis for devising future personnel selection tests for security and defense.

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Received June 2, 2017
Revision received December 18, 2017
Accepted December 18, 2017 ■