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Numerosity adaptation across size transformations

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Numerosity adaptation occurs across sensory modalities and formats, pointing to an abstract and amodal numerosity coding. Recent findings, however, suggest that it may also be shaped by non-numerical visual properties and perceptual categorization. Here, we examined stimulus size because size variations can be interpreted either as feature differences between stimuli or as scale transformations of the same object viewed from different distances. Across two experiments, participants performed a numerosity discrimination task following adaptation to highly numerous dot arrays. In Experiment 1, adaptor and test stimuli consisted of either small or large dots, yielding congruent trials when their size was identical and incongruent trials when it differed. Numerosity adaptation was stronger in congruent than in incongruent trials, indicating that dot size modulates adaptation magnitude, similarly to other visual stimulus properties. In Experiment 2, adaptor size changed dynamically, mimicking the looming-receding motion in depth and promoting object continuity across size transformations. Dynamic size changes did not eliminate the size-dependent modulation of numerosity adaptation. Instead, salient changes in several non-numerical features significantly interact with numerosity processing, shaping aftereffect magnitude. Overall, these findings indicate that numerosity adaptation is a multifaceted phenomenon arising from interactions among numerical information, low-level visual properties, and visual temporal dynamics.

Keywords Numerosity adaptation, Size constancy, Perceptual organization, Object continuity, Size transformation, Adaptor–test congruency.

Humans and animals are highly efficient at perceiving numerosity to roughly estimate how many items are present in visual scenes without serial counting. This nonverbal number sense is an evolutionarily relevant capacity present since early in life: in humans, sensitivity to numerosity is present from birth, arises spontaneously, and can be observed even in individuals without access to formal education, supporting the idea that numerosity is a fundamental dimension of perceptual experience[1–6].

A sense for number is also present in non-human animals: neurophysiological evidence in macaques and crows has identified neurons selectively tuned to numerosity, suggesting the existence of dedicated mechanisms for processing numerical quantity[7–9]. In humans, with the notable exception of a few intracranial recording studies[10,11], evidence for numerosity-selective mechanisms mainly came from psychophysical research. In particular, the adaptation paradigm has been widely used because it can reveal neural populations selective for specific perceptual features and clarify their functional properties. In the case of numerosity, repeated exposure to highly numerous arrays reliably produces aftereffects, with subsequent stimuli being perceived as less numerous, a pattern that has been widely interpreted as evidence for the existence of dedicated mechanisms tuned to numerical quantities[12–15], a possibility further supported by imaging studies[16–18].

Both psychophysical and imaging studies have reported that numerosity adaptation occurs across sensory modalities and formats, suggesting that numerical quantities are represented in a fairly abstract and amodal fashion[13,19]. Neuroimaging evidence also supports relatively abstract numerosity coding across nonsymbolic and symbolic formats[20]. However, subsequent psychophysical findings suggested that this picture may be incomplete, opening a broader debate on the extent to which numerosity adaptation depends on salient stimulus features beyond overall numerical quantity. In particular, numerosity adaptation has been shown to be selectively tuned to salient environmental features: while adaptation to high numerosities was always capable of reducing the perceived numerosity of the following stimuli, this effect was particularly strong when adaptor and test stimuli shared the same color or pitch[21,22]. This congruency effect suggested that non-numerical stimulus dimensions can shape how the aftereffect unfolds[23].

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Caponi et al.[24] further investigated which stimulus properties modulate this congruency effect in numerosity adaptation by manipulating the similarity between adaptor and test arrays across various low-level (luminance, color, shape, and motion profile) and high-level (letters' identity and face expressions) features. Numerosity adaptation aftereffects were observed across all conditions, indicating that the phenomenon cannot be explained by a simple congruent–incongruent distinction. However, their strength was modulated by the congruency between adaptor and test in low-level visual features, whereas higher-level differences had little effect.

Notably, the congruency effect of numerosity adaptation cannot be simply accounted for by changes in perceptual salience between adaptor and test, in that not all salient changes produced the same effects: indeed, differences in motion profile, despite being highly noticeable, did not reliably attenuate adaptation[24]. This suggests that perceptual salience alone is not sufficient to account for the aftereffect, contrary to the predictions of the "old news" hypothesis, which points to numerosity adaptation as a generic consequence of perceptual novelty and salience rather than as a genuine influence of specific visual properties on perceived numerosity[25,26], but see also[22]. Rather, Caponi et al.'s results suggest that some low-level, non-numerical visual properties may play a more prominent role than others in shaping numerosity adaptation[24].

If numerosity adaptation is influenced by some, but not all, low-level salient feature changes, then the critical issue is not only whether adaptor and test differ, but how they actually differ. One possibility is that the determining factor is whether a low-level feature signals a change in stimulus identity. Such a mechanism could offer an ecological advantage, as it may be beneficial to maintain distinct numerical representations for different categories of objects (for example, ripe versus unripe fruits) despite their coexistence within the same environment[27]. Thus, while some manipulations may primarily alter low-level visual properties, others may preserve objects' perceptual continuity despite the physical change. It is therefore important to understand whether reduced adaptation reflects a simple perceptual mismatch or whether it depends on global object-level relations between the adaptor and test stimuli.

Object size provides a particularly informative test case as it can signal a change in object identity or not depending on the context: objects with different sizes can be categorized as different or, alternatively, as the same object seen from different viewing distance yielding different retinal sizes (i.e., size constancy). In the present study, we exploited a numerosity adaptation paradigm while manipulating the relative size between adaptor and test stimuli across two experiments, such that the change could be interpreted either as a feature difference between the stimuli or as a scale transformation preserving object continuity.

In Experiment 1, we presented a static adaptor composed of either small or large dots, followed by test arrays containing fewer dots with either the same or a different dot size. If observers interpreted adaptor and test as distinct objects whose items are characterized by different visual properties, adaptation should be reduced in incongruent compared to congruent conditions, consistent with previous findings for other low-level visual features[24]. Conversely, if the stimuli are interpreted as different scales of the same object, the congruency effect should be attenuated. To anticipate the results, consistent with the first hypothesis, adaptation was significantly reduced when the adaptor and test differed in size.

In Experiment 2, we introduced a dynamic adaptor sequence in which the stimulus gradually expanded and contracted. This manipulation provided a smooth and ecologically plausible size transformation while preserving the spatiotemporal continuity of each dot. Because spatiotemporal continuity is a strong cue to object persistence[28], observers were expected to represent the adaptor and test as the same objects undergoing a coherent change in size rather than as successive objects of different sizes. The ecological relevance of this manipulation is further supported by the sensitivity of the human visual system to looming events[29] and by their capacity to capture attention[30]. Because looming and receding motion may produce different perceptual or attentional effects[30,31], the dynamic adaptor included both phases, minimizing any bias due to motion direction and reducing the likelihood that the observed effects reflect direction-selective adaptation or attentional asymmetries. Importantly, unlike the static manipulation used in Experiment 1, the dynamic manipulation generated substantial changes not only in individual element size but also in aperture area, because near and far objects necessarily occupy different portions of the visual field, with consequent changes in dot density throughout the adaptor sequence. This made the paradigm a particularly stringent test of whether object-continuity cues could overcome a non-numerical, feature-based mismatch between adaptor and test stimuli. Contrary to this prediction, dynamic size transformations did not eliminate the influence of stimulus size on numerosity adaptation. Instead, they revealed a more complex pattern in which the adaptation depended on the temporal structure of the adaptor sequence and its interaction with low-level stimulus properties.

Methods

Participants

A total of 70 participants took part in the study, with 35 participants assigned to Experiment 1 (mean age: 22.54 ± 1.95 years, 16 males) and a separate group of 35 participants assigned to Experiment 2 (mean age: 22.34 ± 1.88 years, 12 males). Sample size was determined a priori using G*Power[32] for a repeated-measures ANOVA with within-subject factors ($f = 0.25$, $\alpha = 0.05$, power = 0.90), indicating a minimum sample size of 30 participants. All participants were naïve to the purpose of the study and reported normal or corrected-to-normal vision. Participants were pre-screened for psychiatric and neurological disorders, and none was taking psychoactive medication at the time of testing. Written informed consent was obtained from all participants prior to participation. The study was approved by the local ethics committee ("Commissione per l'Etica della Ricerca", University of Florence; approval date: July 7, 2020; protocol n. 111) and was conducted in accordance with the Declaration of Helsinki.

Experimental setup

Both experiments were conducted in a dimly lit and acoustically attenuated room. Participants sat at a viewing distance of 57 cm from a 27-inch monitor (resolution: 2560 × 1440 pixels; refresh rate: 60 Hz). Stimuli were generated and presented on an iMac Retina 5 K 27-inch computer (mid-2015 model; 3.3 GHz Intel Core i5 processor; macOS Big Sur 10.12.6; Apple Inc., Cupertino, CA, USA). The experiment was programmed in MATLAB (R2018b; The MathWorks, Natick, MA, USA) using the Psychophysics Toolbox extensions[33,34]. Participants provided manual responses using a standard Apple keyboard.

Stimuli and procedure

In both experiments, stimuli consisted of arrays of non-overlapping dots, half black and half white, displayed against a gray background. The adaptor and reference stimuli comprised 48 and 24 dots, respectively, whereas the test stimulus varied across 11 logarithmically spaced numerosities ranging from 12 to 48 dots (12, 14, 16, 18, 21, 24, 28, 32, 36, 42, and 48). Dot positions were randomly generated on each trial, with a minimum spacing constraint to prevent overlap between elements.

In both experiments, the adaptor duration was set to 2 s. This relatively brief duration was selected to limit participant fatigue and facilitate sustained attention while retaining sufficient exposure to induce reliable adaptation[12,24].

Experiment 1

The first experiment included one baseline condition, in which no adaptor was presented, and two adaptation conditions, in which the adaptor consisted of a static dot array presented within an 8°-radius circular aperture and containing either small dots (0.4° diameter) or large dots (0.8° diameter; Fig. 1A). Because the aperture size remained constant and the adaptor always contained 48 dots, dot density was identical for the small- and large-dot adaptors (0.24 dots/deg^2). During the test phase, test and reference arrays always had the same dot size (either both small or both large) and were presented within the same 8°-radius aperture. Across the range of tested numerosities, the mean dot density was 0.13 dots/deg^2 for both the small- and large-dot test stimuli. Trials were classified as congruent when adaptor and test had the same dot size (small–small or large–large) and as incongruent when adaptor and test had different dot sizes (small–large or large–small).

In baseline trials, participants performed a two-alternative forced-choice numerosity discrimination task while maintaining fixation on a central fixation cross. Test and reference stimuli were presented simultaneously for 500 ms, one on each side of fixation, followed by a 500 ms inter-stimulus interval. In adaptation trials, test and reference were preceded by an adaptor dot array, presented for 2 s at an eccentricity of 10° to the left or right of fixation (Fig. 1B). In all conditions, the task for the participants was to indicate which stimulus appeared more numerous by pressing the left or right arrow on the keyboard.

Each test numerosity was presented 12 times, resulting in 264 trials for each experimental condition and 792 trials overall (~1.30 h total duration). To reduce participant fatigue, the experiment was divided into 10 blocks of approximately 8 min each. The two baseline blocks were always presented first to avoid possible carry-over adaptation effects, whereas the eight adaptation blocks (small/large adaptor × left/right visual field, two

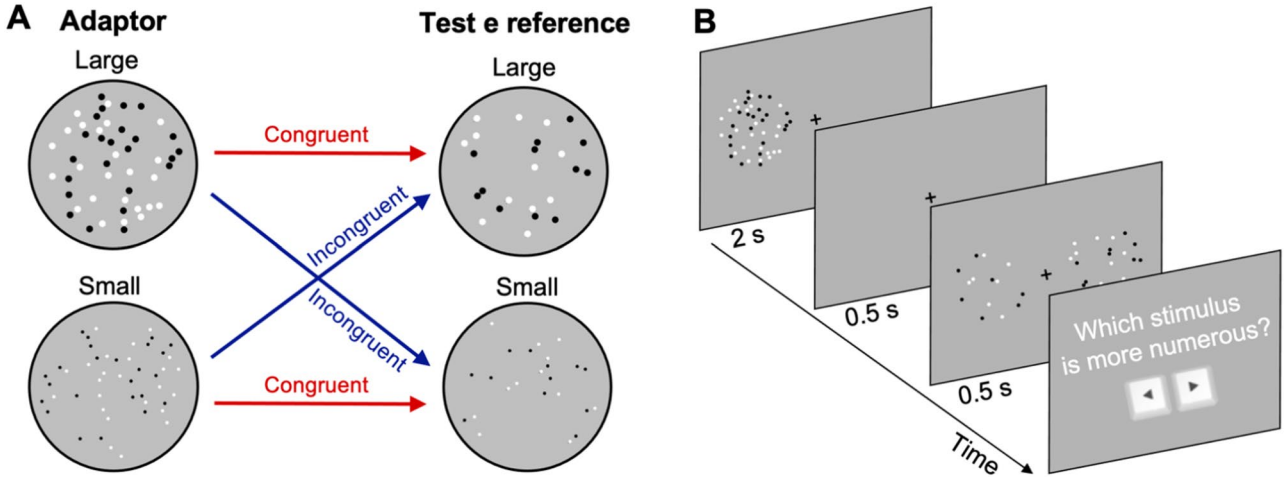

Fig. 1. Experiment 1 – Methods. (A) Stimuli and conditions. The adaptor consisted of either a small-dot or a large-dot array presented within a fixed 8°-radius circular aperture. Test and reference arrays always had the same dot size, generating congruent (small–small; large–large) and incongruent (small–large; large–small) trials depending on the size of the adaptor's dots. **(B) Experimental procedure**. In adaptation trials, participants were exposed to a 2-s adaptor presentation, followed by a 500-ms inter-stimulus interval and then by a 500-ms presentation of the test and reference arrays, and had to indicate which array appeared more numerous. The panel illustrates an example of a congruent trial. In the baseline condition, the same numerosity discrimination task was performed without prior adaptation.

blocks each) were presented in randomized order. Within each block, trials with different test numerosities were presented in random order.

Experiment 2

As in the previous experiment, Experiment 2 included a baseline condition, in which no adaptor was presented, and an adaptation condition. However, unlike Experiment 1, the adaptor was dynamic and consisted of a dot array undergoing looming and receding size transformations designed to promote the interpretation of object continuity across depth (Fig. 2A). During the adaptor sequence (2 s), both dot size and the radius of the circular aperture containing the dots changed continuously across frames, either from small to large and back to small or from large to small and back to large. Specifically, the dot diameter varied from 0.2° to 1°, whereas the aperture radius varied from 5.6° to 10.9°, and vice versa. Because the number of dots remained constant throughout the adaptor sequence, these changes also produced corresponding variations in dot density (dots/deg^2). Thus, the adaptor did not provide a constant level of either dot size or density, but instead continuously modulated both properties over time. Across the adaptor sequence, the mean dot diameter was 0.6°, the mean aperture radius was 8.25°, and the temporal mean dot density was approximately 0.25 dots/deg^2. During the test phase, test and reference arrays were static and always had the same dot size and the same aperture size, which could be either small (0.2° dot diameter; 5.6° aperture radius; mean dot density = 0.26 dots/deg^2) or large (1° dot diameter; 10.9° aperture radius; mean dot density = 0.07 dots/deg^2). Consequently, the average dot diameter and aperture size of the adaptor lay between those of the small- and large-test stimuli, whereas its temporal mean dot density closely matched that of the small-test stimuli and remained substantially higher than that of the large-test stimuli. Trials were classified as congruent when the test matched the initial and final state of the adaptor sequence, and as incongruent when it did not. Thus, congruent trials consisted of small–large–small sequences followed by a small test stimulus and large–small–large sequences followed by a large test stimulus, whereas incongruent trials consisted of small–large–small sequences followed by a large test stimulus and large–small–large sequences followed by a small test stimulus.

Participants performed the same two-alternative forced-choice numerosity discrimination task as in Experiment 1. In adaptation trials, the dynamic adaptor sequence was presented for 2 s at an eccentricity of 13° to ensure that the largest stimulus size did not overlap with the central fixation point during the looming sequence (Fig. 2B).

Each test numerosity was presented 12 times. To reduce participant fatigue, the experiment was divided into six blocks of approximately 10 min each. The two baseline blocks were always presented first, whereas the four adaptation blocks were presented in randomized order. In adaptation trials, the two adaptor sequences (small–large–small and large–small–large) as well as the two test sizes (small and large) were intermixed and presented in random order. Within each block, trials with different test numerosities were presented in random order.

Data processing and statistical analysis

In both experiments, for each participant and condition, we computed, for each test numerosity, the proportion of trials in which the test stimulus was judged more numerous than the reference. Psychometric functions were fitted in MATLAB on log10-transformed test numerosities using a cumulative Gaussian function, and the point of subjective equality (PSE) was defined as the 50% point of the fitted function. Baseline PSEs were also

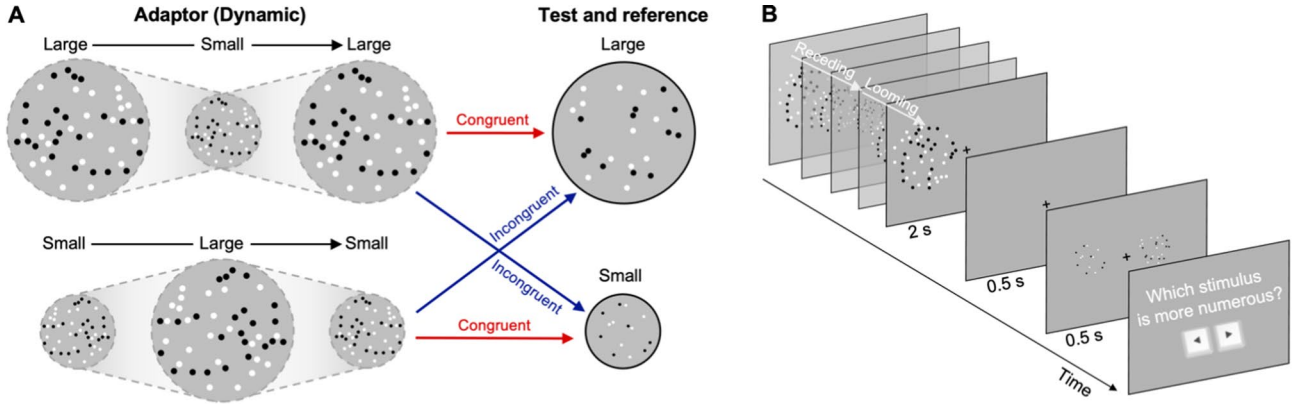

Fig. 2. Experiment 2 – Methods. (A) Stimuli and conditions. The adaptor consisted of a dynamic dot array in which both dot size and aperture size changed continuously, either from small to large and back to small (https://www.youtube.com/watch? v=3J8NcA3Qx3g), or from large to small and back to large (https://www.youtube.com/watch? v=t970wA6YnP8). Test and reference arrays always had the same dot and aperture size, generating congruent and incongruent trials depending on whether the test matched the initial and final state of the adaptor sequence. **(B) Experimental procedure.** In adaptation trials, participants were exposed to a 2-s dynamic adaptor sequence, followed by a 500-ms inter-stimulus interval and then by a 500-ms presentation of the test and reference arrays, and had to indicate which array appeared more numerous. The panel illustrates an example of an incongruent trial. In the baseline condition, the same numerosity discrimination task was performed without prior adaptation.

estimated separately for small- and large-dot trials to assess possible baseline differences between test sizes. PSE estimates were then converted back to the original numerosity scale for reporting. For each adaptor–test size combination, the adaptation effect was quantified as the percentage shift in PSE relative to baseline, computed as $\frac{\mathrm{PSE}_{adapt}-\mathrm{PSE}_{baseline}}{\mathrm{PSE}_{baseline}} \times 100$.

Normality of the adaptation-effect distributions was assessed using Shapiro–Wilk tests and was not violated in any condition (all $p > 0.05$). Therefore, parametric statistics were used throughout. For Experiment 1, a two-way repeated-measures ANOVA was performed on the adaptation effect, with *Dot Size* (large, small) and *Congruency* (congruent, incongruent) as within-subject factors. For Experiment 2, a two-way repeated-measures ANOVA was performed on adaptation effect, with *Adaptor Sequence* (small–large–small, large–small–large) and *Congruency* (congruent, incongruent with respect to the size of the last adaptor frame) as within-subject factors. Effect sizes were estimated using classical eta-squared (η^2). Post hoc pairwise comparisons were conducted using Bonferroni-corrected Student's t-tests, and the effect size of pairwise differences was estimated using Cohen's d.

MATLAB was used for data processing and psychometric fitting, whereas inferential statistics were performed using JASP (Version 0.16.4).

Results

In Experiment 1, we investigated whether changes in dot size between adaptor and test stimuli modulated the magnitude of numerosity adaptation. Figure 3A shows the aggregate psychometric functions across all conditions, collapsed across large- and small-dot stimuli. The proportion of trials in which the test stimulus was judged as more numerous than the reference is plotted as a function of test numerosity. Psychometric functions in adaptation conditions (red and blue lines) were shifted rightward relative to baseline (gray line), indicating that adaptation to high numerosity (48 dots) reduced the perceived numerosity of the subsequent test stimulus. This shift was observed in both congruent and incongruent conditions, meaning that adaptation transferred across changes in dot size. However, the effect was larger when the adaptor and test had matching dot sizes.

To examine adaptation effects separately for small- and large-dot conditions, baseline PSEs were computed independently for the two test sizes. Although the difference did not reach statistical significance ($t(34) = 1.95$, $p = 0.060$; Fig. 3B), adaptation effects were nevertheless conservatively calculated relative to size-specific baselines

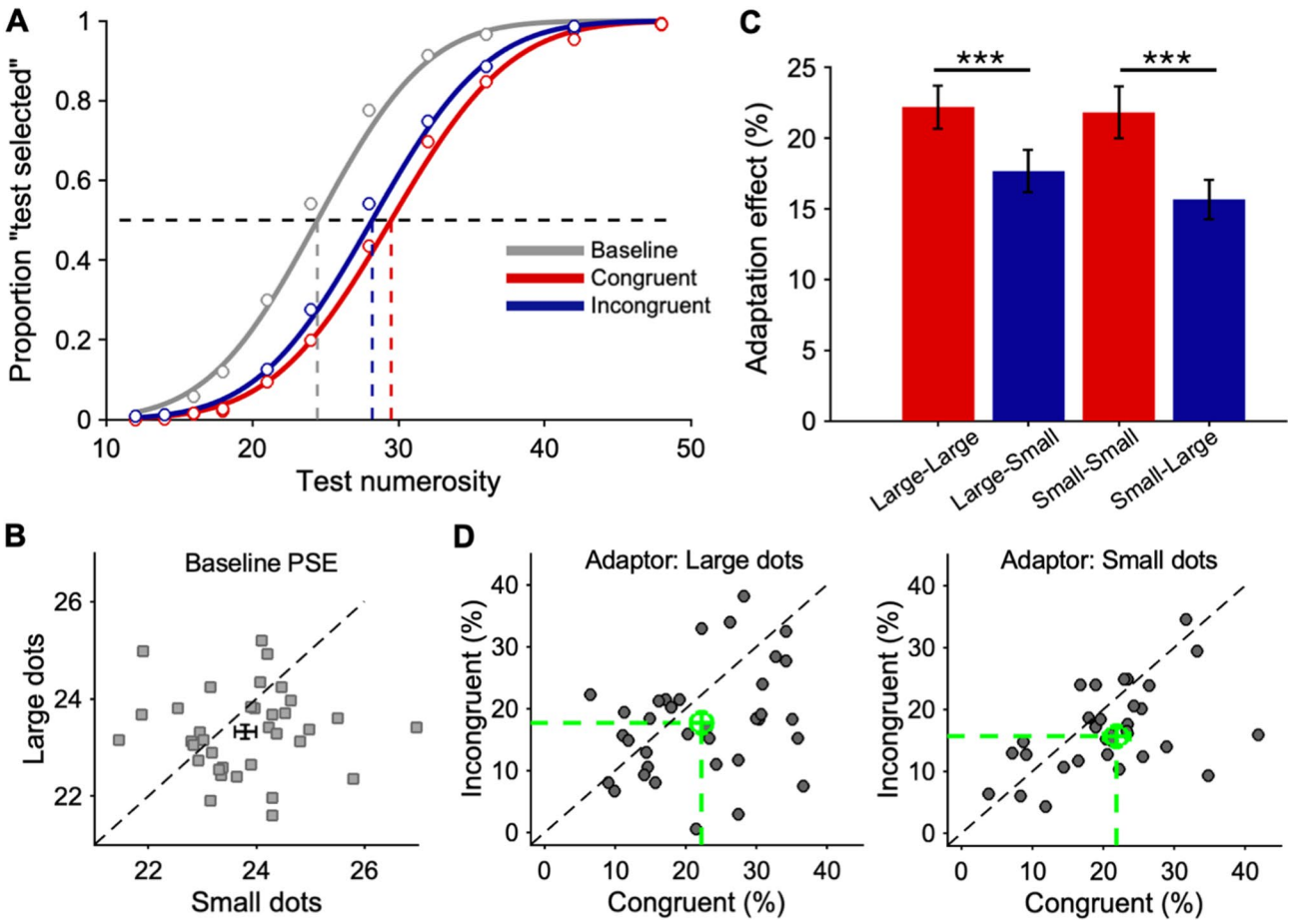

Fig. 3D. further illustrates the relative amount of numerosity adaptation for congruent and incongruent trials separately for large- and small-dot adaptors at the individual-subject level. The congruency effect appears more consistent with small-dot adaptors, whereas large-dot adaptors show greater inter-individual variability.

	Baseline		Adaptation Large dots		Adaptation Small dots	
	Small	Big	Congruent	Incongruent	Congruent	Incongruent
Mean	23.79	23.32	28.48	27.95	28.87	26.91
SEM	0.19	0.15	0.32	0.30	0.33	0.29
Max	26.96	25.19	31.36	31.89	32.38	30.17
Min	21.45	21.60	24.67	23.77	24.71	22.49

Table 1. Descriptive statistics of the points of subjective equality (PSEs) for baseline and adaptation conditions in Experiment 1.

to ensure methodological consistency and control for potential baseline-related biases. Descriptive statistics for the PSEs observed in each experimental condition are reported in Table 1.

Figure 3C shows mean adaptation effects in percentage (± SEM) for congruent and incongruent conditions separately for large- and small-dot adaptors relative to baseline. A two-way repeated-measures ANOVA on adaptation magnitude revealed a significant main effect of *Congruency* ($F(1,34) = 40.59$, $p < 0.001$, $\eta^2 = 0.164$). In contrast, neither the main effect of *Dot Size* ($F(1,34) = 1.63$, $p = 0.211$, $\eta^2 = 0.011$), nor the interaction between the two factors $F(1,34) = 0.28$, $p = 0.599$, $\eta^2 = 0.004$) reached significance. This result indicates that adaptation was reliably weaker in incongruent than in congruent conditions, regardless of adaptor size.

Figure 3. **Experiment 1 – Results. (A)** Psychometric functions obtained by aggregating all participants' responses. The grey curve represents baseline performance, whereas the coloured curves represent adaptation conditions in which adaptor and test dot size were congruent (red) or incongruent (blue). The horizontal dashed line indicates the 50% point used to estimate the PSE, whereas the vertical dashed lines indicate the corresponding PSE values for each condition. A rightward shift relative to baseline indicates reduced perceived numerosity after adaptation. **(B)** Scatter plot showing baseline PSEs for large- and small-dot test stimuli. Each point represents one participant; black error bars indicate the group means ± SEM. The dashed diagonal indicates equality between conditions. **(C)** Mean adaptation effects (± SEM) for congruent and incongruent conditions separately for large- and small-dot adaptors. Asterisks indicate the significant main effect of Congruency revealed by the repeated-measures ANOVA: *** $p < 0.001$. **(D)** Individual-subject scatter plots comparing congruent and incongruent adaptation effects for large-dot (left panel) and small-dot (right panel) adaptors. Each black point represents one participant, whereas green points indicate the group means ± SEM. The dashed diagonal indicates equality between conditions.

The clear congruency effect observed in Experiment 1 suggests that size changes between adaptor and test stimuli may have been interpreted as indicating a change in object identity. In Experiment 2, we therefore sought to create the impression that the same objects were moving in depth by simulating ecologically plausible looming and receding motion. Figure 4A shows the pattern of numerosity adaptation observed in the adaptor dynamic size-transformation condition. As in Experiment 1, psychometric functions in adaptation conditions were shifted rightward relative to baseline, indicating reduced perceived numerosity after adaptation. However, unlike the static condition, congruent and incongruent curves largely overlapped when data were collapsed across the two adaptor sequences.

Baseline PSEs were again computed separately for the two stimulus sizes ($t(34) = 0.38$, $p = 0.706$; Fig. 4B), and adaptation effects were calculated relative to their corresponding size-specific baselines. Descriptive statistics for the PSEs observed in each experimental condition are reported in Table 2.

Mean adaptation effects (± SEM) for congruent and incongruent conditions are shown in Fig. 4C separately for the large–small–large (L–S–L) and small–large–small (S–L–S) adaptor sequences. A two-way repeated-measures ANOVA revealed no significant main effect of *Adaptor Sequence* ($F(1,34) = 0.35$, $p = 0.560$, $\eta^2 = 0.002$) nor of *Congruency* ($F(1,34) = 0.23$, $p = 0.633$, $\eta^2 = 0.002$). However, differently from Experiment 1, a significant interaction between the two factors emerged ($F(1,34) = 14.25$, $p < 0.001$, $\eta^2 = 0.176$).

Post hoc comparisons clarified the nature of this interaction. Within congruent trials, adaptation was significantly stronger following the small–large–small sequence than following the large–small–large sequence ($t(34) = 3.26$, $p = 0.015$, $d = 0.73$). Thus, even when adaptor and test were formally congruent, the two dynamic sequences did not produce equivalent aftereffects. Within the small–large–small sequence, congruent trials produced stronger adaptation than incongruent trials ($t(34) = 3.65$, $p = 0.005$, $d = 0.73$), consistent with the congruency effect observed in Experiment 1. Within the large–small–large sequence, incongruent trials produced numerically stronger adaptation than congruent trials, although this difference did not reach significance ($t(34) = 2.49$, $p = 0.108$, $d = 0.60$). In addition, the two incongruent conditions significantly differed from one another, with stronger adaptation following the large–small–large sequence than the small–large–small sequence ($t(34) = 3.23$, $p = 0.017$, $d = 0.60$). Overall, these results suggest that dynamic size transformations did not straightforwardly eliminate the congruency effect observed in the static condition; instead, they revealed a more complex picture, which modulated both the magnitude and direction of the adaptation effect.

Individual-subject data in Fig. 4D further illustrate this interaction pattern: whereas the small–large–small sequence showed a relatively consistent tendency toward stronger adaptation in congruent than incongruent trials, the large–small–large sequence showed the opposite tendency, with many participants exhibiting stronger adaptation in incongruent trials.

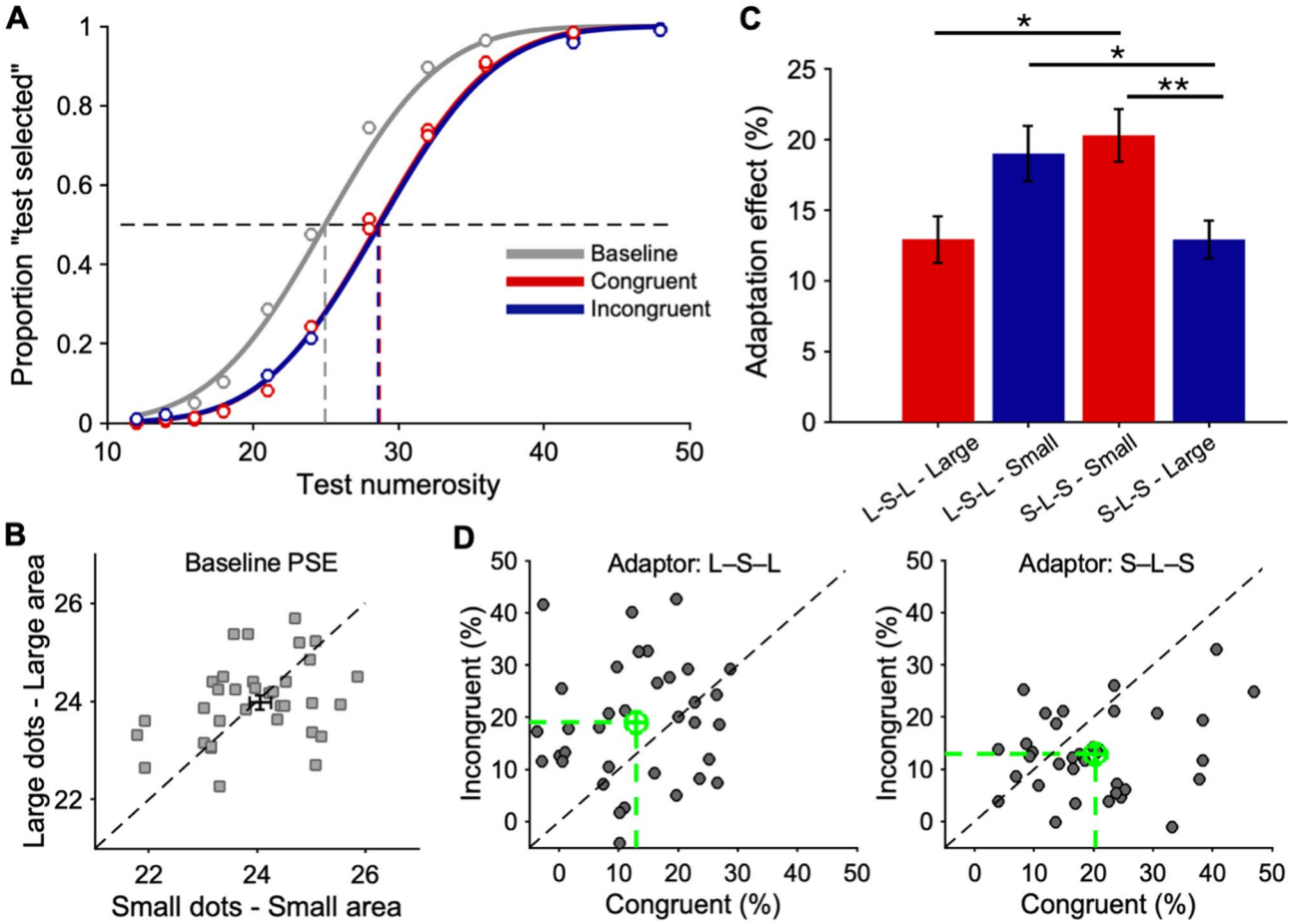

Fig. 4. **Experiment 2 – Results. (A)** Psychometric functions obtained by aggregating all participants' responses. The grey curve represents baseline performance, whereas the coloured curves represent adaptation conditions in which adaptor and test dot size were congruent (red) or incongruent (blue). The horizontal dashed line indicates the 50% point used to estimate the PSE, whereas the vertical dashed lines indicate the corresponding PSE values for each condition. A rightward shift relative to baseline indicates reduced perceived numerosity after adaptation. **(B)** Scatter plot showing baseline PSEs for large-dot (in large area) and small-dot (in small area) test stimuli. Each point represents one participant; black error bars indicate the group means ± SEM. The dashed diagonal indicates equality between conditions. **(C)** Mean adaptation effects (± SEM) for congruent and incongruent conditions separately for large-small-large and small-large-small dot adaptors. Asterisks mark statistically significant post hoc comparisons (Bonferroni correction): * $p < 0.05$, ** $p < 0.01$. **(D)** Individual-subject scatter plots comparing congruent and incongruent adaptation effects for large-small-large (left panel) and small-large-small dot (right panel) adaptors. Each black point represents one participant, whereas green points indicate the group means ± SEM. The dashed diagonal indicates equality between conditions.

	Baseline		Adaptor Large–Small–Large		Adaptor Small–Large–Small	
	Small	Big	Congruent	Incongruent	Congruent	Incongruent
Mean	24.06	23.98	27.08	28.58	28.89	27.05
SEM	0.20	0.14	0.43	0.42	0.38	0.27
Max	27.34	25.69	32.20	34.97	33.89	30.08
Min	21.78	22.27	22.52	23.54	26.01	24.00

Table 2. Descriptive statistics of the points of subjective equality (PSEs) for baseline and adaptation conditions in Experiment 2.

Discussion

The present study investigated whether, and to what extent, numerosity adaptation is modulated by the relative size of adaptor and test stimuli, and whether it generalizes across size transformations designed to promote an object-continuity interpretation. Stimulus size represents a particularly informative test case because variations in size can be interpreted either as changes in low-level visual features that distinguish different stimuli or as scale transformations of the same object viewed from different distances.

In Experiment 1, participants performed a two-alternative forced-choice numerosity discrimination task following adaptation to highly numerous dot arrays. All stimuli were presented under static viewing conditions. In congruent trials, adaptor and test stimuli shared the same dot size, whereas in incongruent trials, an abrupt change in dot size occurred between adaptation and test. Consistent with classical numerosity adaptation effects, adapted stimuli were generally perceived as less numerous than their physical numerosity. Robust adaptation effects were observed in both congruent and incongruent conditions, indicating that numerosity adaptation transferred across changes in dot size. However, adaptation was significantly reduced when adaptor and test stimuli differed in size. These findings are consistent with previous reports showing that the magnitude of numerosity adaptation depends on the similarity between adaptor and test stimuli in terms of low-level visual features[24]. Overall, numerosity adaptation was attenuated when adaptor and test stimuli differed in size, likely because the two displays were categorized as distinct objects, thereby reducing the influence of adaptor numerosity on the estimation of test numerosity.

If differences in stimulus size can modulate the magnitude of numerosity adaptation by affecting the perceived similarity between adaptor and test stimuli, an important question is whether this congruency effect would be reduced when observers are encouraged to interpret size changes not as cues to different objects but as consequences of changes in viewing distance. To address this issue, in Experiment 2, an independent group of participants performed the same two-alternative forced-choice numerosity discrimination task as in Experiment 1, but adaptation was induced by a looming–receding stimulus sequence. The results do not clearly support the hypothesis of a substantial reduction in the congruency effect; instead, a more complex pattern emerged. First, we observed marked differences in adaptation magnitude between the two congruent conditions. Specifically, adaptation was stronger when participants were exposed to an S–L–S adaptation sequence and tested with small elements than when they were exposed to an L–S–L sequence and tested with large elements. Likewise, a significant difference in adaptation magnitude was observed between the two incongruent conditions, in which the size of the test elements did not match the size of the adaptor elements in the first and final frames of the adaptation sequence. Specifically, adaptation was stronger following the L–S–L sequence with a small test than following the S–L–S sequence with a large test. Second, for the S–L–S adaptation sequence, a statistically significant congruency effect was observed, whereas no such effect emerged for the L–S–L sequence. Interestingly, in the latter sequence, incongruent trials produced numerically stronger adaptation than congruent trials, although this difference did not reach statistical significance. Moreover, the adaptation magnitude observed in the congruent L–S–L condition was comparable to that observed in the incongruent S–L–S condition. When these same results were viewed from the perspective of test-stimulus size, a remarkably consistent pattern emerged; the two conditions involving a small test (S–L–S congruent and L–S–L incongruent) produced similarly strong adaptation effects, whereas the two conditions involving a large test (L–S–L congruent and S–L–S incongruent) produced similarly weaker adaptation effects.

How can this pattern of results be explained? The first hypothesis we considered was that adaptation was weighted more strongly toward the final size of the adaptor sequence (i.e., a recency-weighting account). Indeed, this possibility was reflected in the terminology adopted in Experiment 2, where congruent and incongruent conditions were defined according to whether the test stimulus matched the dot size of the final state of the dynamic adaptor. Under this account, the effective adaptor representation would be expected to remain biased toward the terminal size of the sequence. However, this prediction does not accord well with our results. If the final size of the adaptor dominated adaptation, the two congruent conditions would be expected to produce similar aftereffects, as would the two incongruent conditions. Instead, adaptation clustered primarily according to test-stimulus size rather than according to the final size of the adaptor sequence. We therefore considered an alternative hypothesis, namely that observers integrated information about element size across the entire adaptation sequence, effectively adapting to a stimulus characterized by an intermediate element size averaged across frames. Because the S–L–S and L–S–L sequences spanned the same range of element sizes presented in opposite temporal order, such integration would be expected to yield a comparable intermediate adaptor representation for the two sequences. Under this hypothesis, the critical factor would be the relationship between this integrated adaptor representation and the subsequent test stimulus, rather than the temporal order of the adaptor sequence itself. Adaptation to an intermediate adaptor representation may therefore have altered the perceived overall size of the subsequent test stimulus. Specifically, a test stimulus composed of small dots within a small spatial extent may have been perceived as even smaller, enhancing the reduction in perceived numerosity induced by adaptation. Conversely, a test stimulus composed of large dots within a large spatial extent may have been perceived as even larger, partially counteracting the numerosity aftereffect. Overall, this interpretation provides a coherent framework for explaining the observed pattern of results. However, neither the effective size represented across the dynamic adaptor sequence nor its predicted influence on the perceived size of the subsequent test stimulus was directly assessed in the present study. Consequently, this interpretation remains speculative and requires direct experimental validation. Future work directly measuring perceived size under the same adaptation conditions will therefore be necessary to test this hypothesis. We also considered an additional explanation based on dot density. Because the adaptor always contained the same number of dots (48 dots) while its aperture expanded and contracted throughout the looming–receding sequence, dot density necessarily varied across the adaptor sequence. Adaptation to density is well established and has been shown to influence both perceived density and, under some conditions, perceived numerosity[35]. This raises the possibility

that observers adapted to the temporal mean density of the dynamic adaptor or to the density of its last frame. However, these possibilities do not readily account for the observed pattern of results. For the small-test arrays, the temporal mean density of the adaptor closely matched the density of the test stimuli, yet these conditions consistently produced the strongest adaptation effects. For the large-test arrays, the temporal mean density of the adaptor remained substantially higher than that of the test stimuli. Under a purely density-based account, thus assuming a negligible effect of dot size, an adaptor that was both more numerous and denser than the large test arrays might be expected to produce stronger rather than weaker adaptation. Instead, the smallest adaptation effects were consistently observed for the large-test conditions. Thus, temporal mean density alone does not readily explain the observed pattern. We also considered an account based on the density of the final adaptor frame, but this interpretation is likewise inconsistent with the observed pattern of results. The two conditions producing the strongest aftereffects (S–L–S congruent and L–S–L incongruent) terminated with opposite densities, one ending with the highest and the other with the lowest density of the adaptor sequence. The two weakest aftereffects also terminated with opposite densities. Therefore, the magnitude of the aftereffect cannot be straightforwardly explained by the density of the terminal adaptor frame. Overall, it is possible that size and density jointly contribute to perceived numerosity[36]. However, in most cases, their effects are expected to counteract each other, making it difficult to disentangle the relative contribution of these two features within the current paradigm. Future studies specifically designed to orthogonally manipulate size and density will be needed to address this question directly.

Although the explanations discussed above focus on the stimulus properties driving adaptation, an alternative perspective is to ask whether the present findings could emerge from a more general computational mechanism. Divisive normalization represents one such candidate. This canonical computation, whereby a neuron's response is scaled by the pooled activity of neighboring neurons, has been proposed both as a general mechanism of perceptual adaptation[37,38] and, more recently, as a basis of numerosity encoding and adaptation[39,40]. In the model of Park and Huber (2022), responses of difference-of-Gaussians filters across multiple spatial scales are divisively normalized across neighboring units; the summed output is strongly sensitive to numerosity but largely insensitive to item size and spacing, while temporal normalization of this output reproduces numerosity aftereffects. Changes in element size could nevertheless alter the recruitment or weighting of the normalization pool and thereby contribute to the condition-dependent aftereffects observed here. However, current implementations do not straightforwardly predict our size-congruency effects, because their normalization stage largely discounts item size and produces little or no adaptation to size itself[39]. One possibility is that the present effects arise from size-dependent normalization at an intermediate stage, before pooling yields a more size-invariant numerosity representation. Although this possibility cannot be excluded, previous results showing that non-numerical features modulate aftereffect magnitude while numerosity remains its primary driver[24] favor an influence on a numerosity-selective representation rather than adaptation to size per se. Divisive normalization and object continuity should therefore be regarded as potentially complementary: normalization may provide a neural mechanism through which low-level stimulus differences shape adaptation, whereas object continuity may influence how adaptor and test representations are grouped or compared. Explicit simulations of the present paradigm will be needed to distinguish these alternatives.

Taken together, the findings from the two experiments indicate that numerosity adaptation does not fully generalize across size transformations associated with changes in viewing distance. More generally, the present findings reinforce the view that numerosity adaptation cannot be explained by numerical information alone, but reflects the interaction between numerical and non-numerical stimulus properties. In particular, our results are consistent with recent evidence showing that, although numerosity itself is the primary factor driving numerosity adaptation, low-level visual properties can substantially modulate the magnitude of the aftereffect, presumably by altering the similarity between the adaptor and the test stimulus[24]. Importantly, the complex pattern observed in Experiment 2 is less readily reconciled with the old-news hypothesis, according to which numerosity adaptation primarily reflects a filtering mechanism aimed at prioritizing novel visual events[25,26]. Although stimulus size—a highly salient visual feature—clearly modulated numerosity adaptation, its effect depended on the relationship between the dynamic adaptor and the subsequent test stimulus rather than simply on the presence of a salient size change. Thus, the present findings suggest that stimulus salience alone is insufficient to account for the complexity of numerosity adaptation. Consistent with this interpretation, robust numerosity adaptation was observed in all experimental conditions despite systematic changes in low-level stimulus properties across adaptor and test stimuli. These manipulations affected the magnitude of the aftereffect without abolishing numerosity adaptation. Likewise, Burr et al. (2025) reported robust numerosity adaptation even when no spatial overlap existed between adaptor and test elements[41]. Moreover, the filtering account has recently been further challenged by Adriano and Vande Velde[42], who demonstrated substantial numerosity adaptation using adaptors defined exclusively by illusory contours, a condition that effectively rules out explanations based on luminance or contrast masking between adaptor and test stimuli[42]. Taken together, these findings suggest that stimulus similarity shapes the transfer of numerosity adaptation without constituting its primary cause.

The present study has some limitations. First, the dynamic adaptor necessarily introduced several covarying perceptual changes, including motion and continuous variations in element size, aperture size, and dot density. Consequently, the present design cannot fully disentangle the contribution of object-continuity cues from those of these correlated stimulus properties. Second, although the dynamic adaptor was designed on the basis of previous evidence to favour the perception of the elements as persisting objects undergoing a coherent size transformation[28–30], perceived object continuity was not assessed directly. Future studies should explicitly assess this percept while independently manipulating motion, element-size variation, aperture size, dot density, and spatiotemporal continuity to establish their respective contributions. Additionally, because adaptation duration was not manipulated, we cannot exclude that longer exposure might affect the magnitude or pattern of the aftereffect. Although the robust effects observed here and previous evidence[12,24] indicate that 2 s is sufficient

to induce numerosity adaptation, whether the pattern across conditions extends to longer adaptation intervals remains to be established. Finally, the different stimulus eccentricities used in the two experiments may limit their direct comparison, as numerosity perception has been shown to vary with eccentricity[43,44]. However, eccentricity was held constant across all conditions within each experiment and therefore cannot account for the pattern of differences observed within either experiment. Whether the difference in eccentricity between the two experiments also influenced the magnitude of numerosity adaptation cannot be determined from the present data.

In conclusion, we reckon that the present results have broader implications for the study of numerosity perception. Real-world objects and scenes are characterized by multiple perceptual attributes that vary simultaneously, whereas laboratory studies often rely on highly simplified stimuli designed to isolate individual variables. Although this approach is essential for experimental control, it may underestimate the extent to which different stimulus dimensions interact in shaping numerical perception. While some pioneering studies have already moved in this direction[45,46], future research should further investigate numerosity perception using more complex and ecologically valid stimuli. Such an approach may provide a more comprehensive understanding of the factors that determine how numerical information is encoded and processed in natural environments.

Data availability

The datasets generated and analysed during the current study are available in the ZENODO repository: https://doi.org/10.5281/zenodo.21129479.

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Author contributions

S.C., L.I., E.C., and R.A. developed the study concept and contributed to the study design. S.C. and L.I. performed the experiments and analysed the data. S.C. and L.I. drafted the manuscript. E.C. and R.A. contributed to the interpretation of the results and revised the manuscript. All authors reviewed and approved the final version of the manuscript.

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Declarations

Competing interests

The authors declare no competing interests.

Additional information

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