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2 **Title: The interaction between numerical and continuous non-numerical**
3 **magnitudes in a Double Change Detection paradigm**

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16

Abstract

17 In the field of numerical cognition, researchers conventionally assess non-
18 symbolic numerical abilities with the help of number comparison tasks, in which
19 participants need to compare two arrays. Many studies emphasized that visual
20 (non-numerical) dimensions can serve as strategic cues and influence the
21 decision on numerosity in these tasks. In this study, we suggest the use of a
22 novel paradigm based on the Change Detection paradigm. Here, participants had
23 to simultaneously pay attention to numerical changes and visual changes on a
24 target non-numerical dimension (Individual Area, Total Area, Field Area, or
25 Density). Participants had to detect changes relative to the two dimensions and
26 press response keys indicating either number change or visual change or press
27 both keys. In such a double change detection paradigm, and unlike number
28 comparison tasks, target and covarying dimensions cannot serve as cues to
29 influence the numerical decision. We found that numerical change detection was
30 excellent and stable across the conditions. Further, participants were more
31 likely to falsely consider visual changes as numerical changes than the other way
32 around. Lastly, when both dimensions varied, participants more frequently
33 missed visual changes than numerical changes. Overall, our findings show that
34 numerosity was the most salient visual dimension. From a methodological
35 perspective, such a double change detection paradigm could be of critical
36 interest to assess numerical abilities for future studies.

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**The interaction between numerical and continuous non-numerical
magnitudes in a Double Change Detection paradigm**

Humans have a set of abilities dedicated to the representation and manipulation of numerical quantities, which Dehaene (1997) referred to as the *Number Sense*. From a cognitive perspective, the *Number Sense* has largely been assumed to rely on a specific system dedicated to processing cardinality (or *numerosity*): the *Approximate Number System* (ANS, Feigenson, Dehaene, & Spelke, 2004). As its name indicates, the ANS is conceived as a system providing approximate representations of the numerosity for large collections (but see Núñez, 2017, for a critical view on the terminology).

The approximate nature of number representations has notably been highlighted through estimation tasks in which participants are instructed to tell aloud how many items they believe are displayed within a large collection (e.g., Kaufman, Lord, Reese, & Volkman, 1949). Many experimental studies showed that the variability of such numerical estimates increases in proportion to their magnitude (e.g., Gallistel & Gelman, 2000; Platt & Johnson, 1971). In other words, numerical variability is scalar to numerosity: the largest numbers entail the largest fluctuations at the representational level (Feigenson et al., 2004).

Scalar variability is one of the main properties of the ANS. This characteristic has critical implications for the nature of the overlap between two distinct number representations: the overlap does not depend on the numeric distance between two numbers, but on their numerical ratio (Dehaene, 2001). Consequently, the acuity of numerical discrimination is not absolute, but relative to the numerical ratio.

62 Some authors made the most of this property and suggested to use numerical
63 discrimination behavior as a measure of ANS acuity. Among them, Piazza, Izard,
64 Pinel, Le Bihan, and Dehaene (2004) characterized performance – and brain
65 activity – during non-symbolic number comparison tasks with a measure of
66 accuracy across numerical ratios, the Weber fraction. The Weber fraction is the
67 ratio between the amount just noticeably different from a given magnitude, and
68 the magnitude itself (see Stevens, 1957; Van Oeffelen & Vos, 1982). As a
69 constant scaling ratio, the Weber fraction has the advantage of explicitly indexing
70 variability across mental representations (see Whalen, Gallistel, & Gelman,
71 1999). Many authors developed and used similar number comparison tasks
72 during the following years to assess ANS acuity (e.g., Halberda, Mazocco, &
73 Feigenson, 2008; Starr, Libertus, & Brannon, 2013; Winman, Juslin, Lindskog,
74 Nilsson, & Kerimi, 2014). Researchers are still widely relying on non-symbolic
75 number comparison tasks to evaluate general numerical ability (see Guillaume &
76 Van Rinsveld, 2018; for a meta-analysis).

77 Despite their popularity, non-symbolic number comparison tasks have often
78 been criticized (see Gebuis, Cohen Kadosh, & Gevers, 2016; for a review). The
79 main criticism has to do with the inherent relation between numerosity and
80 other non-numerical features within visual stimuli: naturally, an abundant
81 collection is likely to extend over a large space while a depleted collection is
82 likely to occupy much smaller space. Many experimental studies highlighted that
83 these systematic relations are problematic for assessing numerical abilities
84 because numerosity cannot be isolated from other dimensions (Szűcs, Nobes,
85 Devine, Gabriel, & Gebuis, 2013; see Leibovich, Katzin, Harel, & Henik, 2017; for a

review). Among these continuous dimensions, the area occupied by the items (or Total Area, Hurewitz, Gelman, & Schnitzer, 2006; Nys & Content, 2012), the individual item size (or Individual Area, Harvey, Fracasso, Petridou, & Dumoulin, 2015; Henik, Gliksman, Kallai, & Leibovich, 2017), the density within the array (e.g., Durgin, 2008), and the array extent (or Field Area, Gilmore, Cragg, Hogan, & Inglis, 2016) substantially interact with non-symbolic number processing. The precise nature of these interactions is still unsettled, and it remains unclear how continuous dimensions impact number processing. Some authors hypothesized that non-numerical dimensions automatically influence numerical decision at the response selection level (as in a Stroop paradigm, Barth, 2008) but other authors surmised that the effect emerges earlier, at the sensory extraction level (Dakin, Tibber, Greenwood, Kingdom, & Morgan, 2011; Gebuis et al. 2016; Leibovich et al., 2017).

Nonetheless, continuous dimensions not only mindlessly influence number comparison, but they can also be consciously used during the task. A recent study indeed revealed that adults could adaptively use continuous dimensions to help them make a numerical decision (Roquet & Lemaire, 2019; see also Dietrich, Nuerk, Klein, Moeller, & Huber, 2017). Because non-numerical dimensions naturally convey information about numerosity¹, humans can flexibly use these

¹ The information conveyed by a single non-numerical dimension does not systematically predict numerosity. In non-symbolic number comparison tasks, researchers generally make sure that half of the trials are congruent with a given dimension, while the relation is incongruent (or kept constant) for the other half; because of this, it is assumed that the dimension under consideration cannot provide

dimensions – or combinations thereof – as strategic decision cues. Interestingly, some studies reported the existence of the opposite causal relation between numerical and non-numerical dimensions, where numerosity influences the comparison of other physical properties (such as total area, Guillaume, Nys, Mussolin, & Content, 2013; Nys & Content, 2012). Depending on the context, the number can also serve as a strategic cue to solve non-numerical tasks. From the strategic perspective, any feature from a visual scene, however irrelevant to the task, can intentionally be used as a cue to get additional information to make a decision. It is thus not possible to isolate one dimension from the others using comparison tasks.

To overcome this issue, we describe in the current study a behavioral assessment based on the change detection paradigm (Luck & Vogel, 1997; Phillips, 1974). In this paradigm, participants were instructed to make a decision based not on one target dimension (i.e., number), but on two dimensions (i.e., number and one non-numerical feature). In particular, we presented a sequence of arrays that all had the same visual characteristics (see Method) and we introduced rare stimuli that could either deviate in numerosity, in a continuous visual dimension, or in both. Accordingly, participants had to detect number changes, visual changes, or changes in both dimensions. The main objective of such a paradigm is to directly contrast processes devoted to number change detection (i.e., visual, attentional, decisional, and response reliable information about number throughout the task (see for instance Piazza et al., 2004; for further methodological considerations; but see Gebuis et al., 2016 for several methodological concerns).

selection processes) and those devoted to the other changing dimension. Furthermore, because double responses are possible (i.e., when both dimensions under consideration vary at the same time), we can assess whether and how the changes were integrated. We thus aim at measuring whether and how numerosity competes (i.e., number change vs. non-numerical change) and interacts (i.e., double change) with other visual properties.

When manipulating number and a given visual dimension, one additional dimension necessarily covaries with the manipulated variables. For instance, when manipulating Number (N) and Individual Area (IA), Total Area (TA) systematically varies as a function of N and IA, since $TA = N \times IA$ (see DeWind, Adams, Platt, & Brannon, 2015, for discussion and modeling). However, in such a double change detection task, any change in the covarying dimension – TA – would merely indicate that there was a change but importantly, it would not provide enough information to determine the nature of the change. Thus, a change in Total Area would indicate that there was a change in the displayed array, but it would not allow distinguishing whether Number, Item Area, or both changed (see Figure 1). Therefore, the covarying dimension cannot serve as a cue to make the required choice between number changes and target visual dimension changes (see Method and Supplementary Material for detailed explanation). This is a substantial advantage over traditional comparison tasks, in which covarying dimensions interfere at the trial level with the numerical judgment (Barth, 2008; Gebuis *et al.*, 2016; Leibovich *et al.*, 2017) and can be intentionally used (Roquet & Lemaire, 2019).

Numerosity	Individual Dot Area				
	65	90	120	160	220
13	NV 845	NV 1170	N 1560	NV 2080	NV 2860
	NV 1170	NV 1620	N 2160	NV 2880	NV 3960
18	V 1560	V 2160		V 3840	V 5280
	NV 2080	NV 2880	N 3840	NV 5120	NV 7040
24	NV 2860	NV 3960	N 5280	NV 7040	NV 9680
32					
44					

Figure 1. Principle of the manipulation with Number and Individual Area. The same ratios are used to determine values on both dimensions. Numbers in cells display the Total Area (i.e., Number $\times$ Individual Area). Letters in cells indicate the expected response (N: numerical change; V: visual change; NV: bi-dimension change). The color code highlights Total Area values. These values cannot differentiate between numerical and visual change, as it is identical in paired cells on the positive diagonals.

In this study, we individually compared numerosity to four critical visual features following the analysis by DeWind and colleagues (2015): Total area, Individual Area, Field Area, and Density. We thus developed four different conditions in which number and each of these four dimensions were manipulated. We aim at comparing the patterns between the four conditions, to investigate whether numerical-visual interaction and/or competition is stable across the visual features, or whether it depends on the visual property under consideration.

164

Method**165 Participants**

166 We recruited 114 undergraduate students with a normal or corrected vision who
167 participated for course credits. We evaluated participants' numerical ability with
168 the Panamath software (based on Halberda et al., 2008) and we checked the
169 presence of any learning disabilities with a short questionnaire. We excluded 14
170 participants who performed at chance in the Panamath task (*i.e.*, reaching less
171 than 60% overall accuracy), and we further excluded 6 participants who
172 reported suffering or having suffered from learning disabilities such as
173 dyscalculia or dyslexia. Additionally, we had to exclude 14 participants due to
174 poor instruction compliance (*i.e.*, responding to each trial, or following a
175 systematic and irrelevant response pattern) during the experimental conditions.
176 The final sample consisted of 80 young adults (mean age = 19.7 years, Standard
177 Deviation (SD) = 1.69, 8 males). We formed four groups of twenty participants,
178 each taking one of the four experimental conditions. We followed APA ethical
179 standards to conduct the present study. The Ethics Committee of the Faculty of
180 Psychological Sciences, Université Libre de Bruxelles, approved the study before
181 the start of data collection.

182 Apparatus

183 Participants were tested in a large room in small groups of five or six, for an
184 approximate duration of one hour and thirty minutes. Each participant
185 comfortably sat in front of a computer screen, isolated from the other ones by
186 way of separation panels. The experiments were designed with Psychopy scripts

(Peirce et al., 2019) running on Python. Stimuli were displayed on a 19-in screen with a resolution of 1280×1024 px. Responses were recorded through ioLab Systems button boxes. All statistical analyses were conducted with JASP (JASP Team, 2018).

Material and procedure

We designed four change detection conditions, one for each continuous dimension of interest: The Total Area (TA) occupied by the dots, the Individual Area (IA), the size of the Field Area (FA), and the Density (D). The four TA, IA, FA, and D conditions had similar instructions and procedures: participants were asked to look at the screen where dot arrays would be successively displayed and to pay attention to specific changes that could occur within the sequence. In particular, participants were told that most dot arrays would obey specific construction rules regarding the number of dots and regarding the visual feature under consideration (*i.e.*, the target continuous dimension) and that some arrays would conversely diverge from one or both construction rules. We also emphasized that the task concurrently involved both number and one continuous dimension change detection. Finally, participants were instructed to report number changes by pressing one button, target continuous dimension changes by pressing another button, and simultaneous (double) changes by pressing both buttons. Conversely, if they thought that there was no change, they had to press no button.

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Figure 2. Illustration of example stimuli for the Density condition (upper left), Field Area condition (upper right), Individual Area condition (lower left), and Total Area condition (lower right). The x-axis represents the visual ratio, and the y-axis represents the number ratio. The standard is emphasized for each condition at the center of the matrix.

In each condition, we presented eight blocks of 160 stimuli (128 standards and 32 deviants), for a total of 1,280 stimuli (1,024 standards and 256 deviants).

Stimuli consisted of 1050×1050px images with dark blue dots (RGB=3-37-82) displayed on light blue background (188-185-255). Standard stimuli always

contained 24 dots and followed a specific construction rule as a function of the condition: in the TA condition, standard total area was 134.3 Kp (kilopixel); in

the IA condition, standard individual area was 3.5 Kp; in the FA condition,

standard field area was 1,238 Kp (with a tolerance of 2%); and in the D

condition, standard density was 0.0036 Kp. We constructed the deviant stimuli

by varying either numerosity or the target dimension, or both together; the variation could either have a small ratio of 1.3 (or 1/1.3) or a large ratio of 1.8 (or 1/1.8). Examples are provided in Figure 2. Within the sequences, two to six standard stimuli were displayed between successive deviants. Each array was presented on the screen for 500ms, and the inter-stimuli interval was 1500ms. Participants had the opportunity to press buttons or to refrain from doing so until the onset of the next trial (2000ms in total). Figure 3 illustrates a sequence contrasting Number and Individual Area (IA condition).

Figure 3. Illustration of a stimulus sequence for the Individual Area (IA) condition.

Within the sequence, two to six standard stimuli are displayed between deviants. Stimuli can deviate in numerosity, IA, or both (i.e., double changes). Participants press one button for numerosity changes and another for IA changes. They have to press both buttons for double changes.

During instruction, participants were shown three standard collections and six deviant collections (one lower and one higher than the standard for each of the three change categories) as examples. The experiment started with three short training blocks of 40 items (32 standard and 8 deviant stimuli) with feedback (i.e., correct, incorrect, or incomplete answer). The order of the experimental blocks and the assignment of the response buttons (left or right) was

randomized and counterbalanced across participants. Participants had the opportunity to take a short break between blocks.

Two sensitivity indices (d')

Accuracy may not be an adequate index of performance in change detection paradigms, since participants who systematically respond to every trial would unjustifiably obtain the perfect score of 100% correct. It is thus essential to take false alarm rates into account (i.e., responses occurring when there is no change and no response is expected). In particular, the present detection task involved deliberate responses to two kinds of change (either related to the number or a given visual property of the stimulus), so there are two false alarm rates (i.e., erroneously reporting a number change and erroneously reporting a visual change). Critically, these numerical and visual false alarm rates might naturally be unbalanced. This is likely since adults spontaneously show a preference for processing numerosity over other visual dimensions (Cicchini, Anobile, & Burr, 2016; Ferrigno, Jara-Ettinger, Piantadosi, & Cantlon, 2017). We thus needed to ascertain that differences in cue prominence would not bias the results, and we consequently computed measures of performance that accounted for false alarm rates.

We adapted the computation procedure of the sensitivity index (d' , Green & Swets, 1988, see MacMillan & Creelman, 2004; and also see Wickens, 2001) to get a measure of sensitivity for each of the two simultaneous detection processes, hence getting both a number d' and a visual d' . To do so, we separately coded the button presses for number and visual changes as a function of the nature of the change (see Table 1). In particular, to obtain d'_{Num} , we first

computed the Hit rate (H) by dividing the total count of correct number change detections (sum of cells labeled H_{Num} in Table 1) by the total count of number change trials (i.e., the count of correct detections added to the count of number change misses, M_{Num}). We computed the False Alarm (FA) rate by dividing the total count of false alarms (FA_{Num}) by the count of trials without number change (i.e., the count of false alarms plus the count of correct rejections, CR_{Num}). In a third and final step, we computed $z(H_{Num}) - z(FA_{Num})$ to get d'_{Num} . We repeated the same steps to compute in a similar way d'_{Vis} , focusing here on visual changes. Number d' and visual d' are two independent measures of number sensitivity detection and visual sensitivity detection, respectively.

Table 1. Coding of responses for the calculation of d' 's.

Response	Change nature			
	No change	Number change	Visual change	Double change
No response	CR_{Num}	M_{Num}	CR_{Num}	M_{Num}
	CR_{Vis}	CR_{Vis}	M_{Vis}	M_{Vis}
Number response	FA_{Num}	H_{Num}	FA_{Num}	H_{Num}
	CR_{Vis}	CR_{Vis}	M_{Vis}	M_{Vis}
Visual response	CR_{Num}	M_{Num}	CR_{Num}	M_{Num}
	FA_{Vis}	FA_{Vis}	H_{Vis}	H_{Vis}
Double response	FA_{Num}	H_{Num}	FA_{Num}	H_{Num}
	FA_{Vis}	FA_{Vis}	H_{Vis}	H_{Vis}

Note. CR = Correct Rejection; FA = False Alarm; H = Hit; and M = Miss.

278

Results

279 Table 2 summarizes the performance in the four conditions. As mentioned in the
 280 Method section, accuracy and latency may not be adequate indices of
 281 performance in change detection paradigms. We thus do not analyze these
 282 indices here for the sake of brevity; Supplementary Material (section B) provides
 283 detailed analyses of performance (accuracies and latencies) for every condition.

284 **Table 2. Descriptive statistics.**

Condition	Type of trial	Measure	
		Accuracy (in percent)	Latency (in ms)
Individual Area	No change	98 [97, 99]	-
	Number change	57 [51, 64]	873 [803, 942]
	Visual change	43 [35, 52]	895 [833, 958]
	Double change	25 [19, 30]	972 [893, 1051]
Total Area	No change	97 [96, 99]	-
	Number change	40 [33, 47]	923 [837, 1010]
	Visual change	24 [18, 30]	954 [802, 1106]
	Double change	19 [12, 27]	1032 [919, 1145]
Field Area	No change	97 [95, 100]	-
	Number change	51 [45, 57]	935 [866, 1004]
	Visual change	34 [28, 41]	909 [846, 973]
	Double change	20 [14, 26]	975 [868, 1082]
Density	No change	98 [96, 99]	-
	Number change	43 [37, 49]	1058 [993, 1123]
	Visual change	36 [30, 41]	1079 [1007, 1151]
	Double change	17 [13, 22]	1109 [1004, 1215]

285 Note: Latencies are expressed in terms of correct response times. Mean response latency was

286 considered when participants pressed both buttons. Brackets depict 95% confidence intervals.

287 Sensitivity analysis

288 For each condition, we computed a numerical d' and a visual d' (see Method). In
 289 the Individual Area condition, mean d'_{Num} was 2.33, 95% CI [2.14, 2.52] and d'_{Vis}
 290 was 2.50, 95% CI [2.28, 2.73]. In the Total Area condition, d'_{Num} was 2.16, 95% CI
 291 [1.96, 2.35] and d'_{Vis} was 1.51, 95% CI [1.22, 1.80]. In the Field Area condition,
 292 d'_{Num} was 2.22, 95% CI [2.07, 2.36] and d'_{Vis} was 2.13, 95% CI [1.92, 2.33].
 293 Finally, in the Density condition, d'_{Num} was 2.32, 95% CI [2.09, 2.56] and d'_{Vis} was
 294 1.81, 95% CI [1.65, 1.96]. Corresponding data are illustrated in Figure 4.

295 We conducted an ANOVA on d' values with Condition (four levels) as between-
 296 subject factor and Type of Change (two levels: number or visual) as within-
 297 subject factor. The analysis revealed that condition had a significant effect on d'
 298 values, $F(3, 66) = 7.821, p < .001, \eta^2 = .26$. The type of change also had a
 299 significant effect, $F(1, 66) = 30.660, p < .001, \eta^2 = .21$, and the interaction was
 300 significant, $F(3, 66) = 15.140, p < .001, \eta^2 = .320$. Simple main effect analyses
 301 (with pooled error) showed that the type of change did not significantly affect d'
 302 values during Individual Area and Field Area conditions, respectively $F(1,66) =$
 303 3.440, $p = .068$ and $F < 1$. Despite of this, the type of change significantly affected
 304 d' values during the Total Area and Density condition, respectively $F(1,66) =$
 305 38.169, $p < .001$ and $F(1,66) = 28.950, p < .001$. In other words, participants
 306 detected numerical changes significantly better than changes relative to two
 307 visual dimensions (namely, Total Area and Density).

308 It is worth noting that numerical d' values were quite stable while visual d'
 309 values fluctuated across the conditions. Pairwise *post-hoc* tests confirmed that
 310 there were no significant differences in d'_{Num} across conditions, all $ps \approx 1$. Yet

there were significant differences for visual d' between Individual Area and Density conditions, $t = 5.147$, $p < .001$, between Individual Area and Total Area, $t = 7.017$, $p < .001$, and between Total Area and Field Area, $t = 4.308$, $p = .001$.

314

315 **Figure 4. Values of d'_{Num} (white dots) and d'_{Vis} (black dots) as a function of the condition.**

316 **Vertical lines depict the 95% CI.**

In addition to the sensitivity indices, we computed two indices allowing to better characterize performance: *False Nature Attributions*, and *Partial Omission Rates*. We report these additional results in the following sections.

320 False Nature Attributions

When only one dimension changed, one interesting mistake could occur: the erroneous attribution of the type of change to the dimension that did not change (e.g., responding that numerosity changed while it was the visual dimension that changed). Although the attribution of the type of change was erroneous, these responses remain a marker of change detection; it thus seems interesting to consider them in the analyses. We coded such responses as *False Nature*

327 *Attributions* (FNAs) and distinguished numerical FNAs (i.e., numerosity detection
 328 on visual changes) from visual FNAs (i.e., visual detection on numerical changes).
 329 In the Individual Area condition, numerical FNA was 13%, 95% CI [8, 19], and
 330 visual FNA was 3%, 95% CI [1, 4]. In the Total Area condition, numerical FNA
 331 was 20%, 95% CI [15, 25], and visual FNA was 14%, 95% CI [9, 19]. In the Field
 332 Area condition, numerical FNA was 14%, 95% CI [10, 18], and visual FNA was
 333 11%, 95% CI [7, 16]. Lastly, in the Density condition, numerical FNA was 11%,
 334 95% CI [7, 14], and visual FNA was 11%, 95% CI [7, 16] (see Table 3). We
 335 conducted a repeated-measure ANOVA with Type of change (two levels,
 336 numerical or visual) as within-factor, and Condition (four levels) as a between-
 337 factor to verify this pattern. Results confirmed such an erroneous numerical
 338 preference because the type of change had a significant effect, $F(1, 76) = 16.580$,
 339 $p < .001$, $\eta^2 = .08$. It should be noted that FNAs differed as a function of the
 340 condition, $F(3, 76) = 6.672$, $p < .001$, $\eta^2 = .20$, with more FNAs in the TA
 341 condition, but there was no significant interaction, $F(3, 76) = 2.377$, $p = .077$, $\eta^2 =$
 342 .03. Overall, in the first three conditions, numerical FNAs were more frequent
 343 than visual FNAs, which suggests that participants naturally tended to falsely
 344 attribute a change to the numerosity rather than any visual property.

345 **Partial Omission Rates**

346 Another interesting mistake that could occur when both dimensions changed is
 347 the omission of one dimension in the response. In this situation, participants
 348 detected that there was a change in one dimension but failed to detect the
 349 change in the other. To evaluate whether and how frequently participants
 350 reported only one change detection – and thus missed the other change –, we
 351 computed a numerical and a visual *Partial Omission Rate* (POR). POR_{Num} indexes
 352 the percentage of omissions of the numerosity change while the visual change
 353 was detected, and POR_{Vis} indexes the percentage of misses of the visual change
 354 while the numerical change was detected. For the sake of simplicity, and to
 355 avoid any unbalance in the expected attentional weight on both dimensions in
 356 further analyses, we only considered for this measure trials involving double
 357 changes with the same ratio (i.e., either number ratio of 1.3 and visual ratio of
 358 1.3, or number ratio of 1.8 and visual ratio of 1.8).

359 In the Individual Area condition, numerical POR was 22%, 95% CI [17, 27], and
 360 visual POR was 34%, 95% CI [27, 40]. In the Total Area condition, numerical
 361 POR was 18%, 95% CI [13, 22], and visual POR was 39%, 95% CI [34, 45]. In the
 362 Field Area condition, numerical POR was 26%, 95% CI [21, 30], and visual POR
 363 was 32%, 95% CI [28, 36]. Lastly, in the Density condition, numerical POR was
 364 20%, 95% CI [16, 24], and visual POR was 40%, 95% CI [34, 46] (see Table 3). A
 365 repeated-measure ANOVA with Type of Change (two levels, numerical or visual)
 366 as within-factor, and with Condition (four levels) as between-factor confirmed
 367 this numerical advantage, $F(1, 76) = 49.633$, $p < .001$, $\eta^2 = .28$. There was no
 368 significant condition effect, $F < 1$, but the interaction reached the significance

level, $F(3, 76) = 2.766, p = .048, \eta^2 = .04$, mostly due to the larger discrepancies in the TA condition and the D condition. In a nutshell, the visual POR was systematically larger than the numerical POR, which suggests that participants were more likely to overlook the visual dimension during double changes.

Table 3. False Nature Attributions and Partial Omission Rates.

Condition	False Nature Attributions		Partial Omission Rates	
	Numerical	Visual	Numerical	Visual
Individual Area	13 [8, 19]	3 [1, 4]	22 [17, 27]	34 [27, 40]
Total Area	20 [15, 25]	14 [9, 19]	18 [13, 22]	39 [34, 45]
Field Area	14 [10, 18]	11 [7, 16]	26 [21, 03]	32 [28, 36]
Density	11 [7, 14]	11 [7, 16]	20 [16, 24]	40 [34, 46]

375

Discussion

376 In the current study, we aimed at comparing numerical processing to non-
377 numerical processing in a double change-detection paradigm. We computed
378 three indices which highlighted three findings: First, sensitivity indices revealed
379 that participants were at least as good or better at detecting numerical changes
380 than changes related to non-numerical properties. Second, participants
381 committed more attribution errors in favor of numerosity than errors in favor of
382 the target visual dimension (except in the Density condition where the rates
383 were about equal). Third, participants systematically missed more visual
384 changes than numerical changes in double change trials, meaning that they
385 tended to overlook visual features rather than numerosity when both properties
386 were fluctuating.

387 The findings support that, for a given ratio, adults are at least as sensitive, or
388 even more sensitive, to number changes than to visual changes. Because our
389 paradigm allows for a direct comparison of detection processes of two given
390 dimensions, the robust advantage for number detection provides evidence that
391 number is the most salient dimension amongst the ones considered. One could
392 argue that the salience of number could be due to a general decisional bias in
393 favor of numerosity in the case of uncertainty, but then we should have observed
394 similar proportions of false number attribution across the conditions. This was
395 not the case; it is thus unlikely that general decisional processes account for this
396 preference. This 'numerical advantage' is actually in line with previous
397 observations that adults spontaneously show a preference for processing
398 numerosity over other visual dimensions (Cicchini *et al.*, 2016; Ferrigno *et al.*,

2017). Such a substantial number salience has also been observed in young children (Cordes & Brannon, 2009), and number salience might become even greater in adults who *learned to focus* on numerosity (see Piazza, De Feo, Panzei, & Dehaene, 2018).

Sensitivity analyses provide further insights about the interaction between number and continuous dimensions processing. One interesting observation is that number d' was constant across the conditions. This means that number detection was not affected by the other concurrent detection task, nor by the nature of the covarying dimension. This is an important observation because it directly supports our claim that participants could not efficiently use the covarying dimension as a cue to solve the task. From a methodological point of view, the present double change detection paradigm seems to do a better job than standard numerical comparison tasks in isolating numerical perceptual and decision processes. In numerical comparison tasks, participants strategically and deliberately use covarying visual dimensions as cues (Roquet & Lemaire, 2019), so that the effect of visual cues observed in numerosity comparison tasks stems from the subjective perspective (Dormal, Larigaldie, Lefèvre, Pesenti, & Andres, 2018). Future studies could thus use and develop similar paradigms to evaluate the relation between number discrimination and more elaborated mathematical abilities.

Sensitivity analyses further revealed that visual d 's were highly dependent on the dimension under consideration. Both Total Area d' and Density d' were significantly lower than Number d' . This means that Total Area and Density changes were significantly less efficiently detected than numerical changes.

Discrepancies between visual and numerical d' are not surprising, since many studies showed that number processing is independent of area processing (Odic, Pietroski, Hunter, Lidz, & Halberda, 2013) and density processing (e.g., Anobile, Castaldi, Turi, Tinelli, & Burr, 2016). Remarkably, visual d' reached a value similar to numerical d' in the Field Area condition and the Individual Area condition. In other words, changes related to these two dimensions were as easily detected as changes related to numerosity. Once again, this is not surprising because evaluating Individual Area ultimately consists of evaluating only one element and evaluating Field Area consists of evaluating the whole array globally as a single object. We can assume that these evaluations are fast and efficient, allowing greater sensitivity. Crucially, the sensitivity for these salient dimensions was at the same level as numerosity sensitivity, which corroborates the claim that number is a salient property from the visual scene (Cicchini *et al.*, 2016; Ferrigno *et al.*, 2017).

Finally, we need to mention that we observed a significant ratio effect across the conditions (see Supplementary Material B). As one could expect, small changes were less often detected than large changes. Future studies should evaluate in more detail the interplay between number and non-numerical visual features by using a greater variety of ratios. Because it makes the covarying visual dimension uninformative about the type of change conveyed, the double change detection paradigm seems indeed very promising in measuring number discrimination thresholds more precisely. Future studies could expand current results by assessing a broader range of numerical and visual ratios.

446 To conclude, the present findings support the view that number is a salient
447 property from the visual scene that adults can process and explicitly evaluate
448 with success. Since we observed stable numerical sensitivity across four
449 different conditions whereas visual sensitivity depended on the visual property
450 under consideration, we conclude that numerical change detection does not
451 depend on unspecific visual change detection. From a methodological
452 perspective, double change detection paradigms offer a promising novel design
453 to isolate number perceptual and decisional processing from covarying visual
454 processing.

455

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