The Nature of Garner Interference: The Role of Uncertainty, Information, and Variation in the Breakdown in Selective Attention

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Ruining head: Interference and information

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Abstract

The popular measure of Garner Interference specifies the detriment to performance with the task-relevant attribute in the presence of a randomly varying distractor. But is irrelevant variation per se responsible for this breakdown of selective attention as the traditional account suggests? In this study we identified an overlooked alternative account – increased irrelevant information – which threatens the validity of the variation interpretation. We designed a new condition within the Garner paradigm, *Roving Baseline*, which allowed for dissociating the separate and combined contributions of information and variation at both macro and micro levels of analysis. A third account, increased number of stimuli or stimulus uncertainty, was also considered as well as the rival interpretations of configural processing and change detection. Our conceptual assay was complemented by a pair of dedicated experiments that included the novel Roving Baseline condition. The results of the theoretical analysis and of the experiments converged on supporting variability as the source of Garner interference. We found no evidence for an influence of information or of stimulus uncertainty. Our study thus adds further support for W. R. Garner's original intuition when designing the paradigm and the interference bearing his name.

Keywords: Garner-interference, information, distractors, stimulus uncertainty

The Nature of Garner Interference: The Role of Uncertainty, Information, and Variation in the Breakdown in Selective Attention

Selective attention is indispensable for adaptive functioning in everyday life. When crossing the road, one must focus on the speed of the approaching car and ignore such momentarily irrelevant dimensions as the car's make, shape, or color (the latter may well be the relevant dimension when purchasing a car). In the absence of selective attention, one cannot read the newspaper in the cafeteria, follow a presentation in class, or negotiate the traffic while walking or driving. A popular toolkit for evaluating the selectivity of attention is *Garner's Speeded Classification Paradigm* (Garner, 1970, 1974, 1976; see Algom & Fitousi, 2016, for review). A key assay in this paradigm is *Garner Interference* (GI), which indexes intrusions by an irrelevant distractor on performance with the task-relevant dimension. The larger the GI, the greater is the failure to attend fully selectively to the target dimension. Our goal in this work was twofold. First, we considered different possible sources of GI, providing analyses at both macro and micro levels of global and trial-to-trial performance. The former is the standard analysis of overall performance in the various conditions of the Garner paradigm, whereas the latter assesses local sequential effects missed in the global analysis. We complemented the theoretical explorations by a pair of Garner experiments aimed at deciding between the alternatives unearthed in the analysis.

Garner's Speeded Classification Paradigm and Garner Interference

Suppose that you are presented with shapes in color and that your task is to name the color. In one block of trials, *Baseline* (B), the task-irrelevant dimension of shape is held constant throughout the block (say a triangle appears on all trials) so that only the target dimension of color varies in a random fashion from trial-to-trial. In a second block, *Filtering* (F), both the relevant (color) and the irrelevant (shape) dimensions vary from trial to trial in a random fashion (e.g., for shape: a triangle appears on some trials, circle on other trials; for color: red on some trials, green on other trials – but the dimensional values are not correlated). If color performance is on a par in B and F, then selective attention to the color is said to be perfect. The parity shows that task-irrelevant variation (in F) did not take a toll on responding to the target color. However, if performance in F is worse than that in B, fully selective attention to color has failed. This difference in performance between B and F (favoring the former) is called GI (defined by Equation 1)

$$GI = MRT(F) - MRT(B) \qquad (1)$$

where MRT is the mean correct reaction time to color.

The standard Garner paradigm includes a third condition, *Correlation*. In this condition, values of the target and the irrelevant dimension vary from trial-to-trial, but they do so in a correlated fashion. For example, on all trials where the color is red the shape is triangle. Our focus in this study was the nature of Baseline and, consequently, of the way it shapes Garner Interference, hence, we did not run the Correlation condition in the current experiments. However, we do consider this condition, too (see Figure 1 and Table 1), and discuss it along with several theoretical ramifications when reviewing the results as a whole.

In Figure 1, we provide an illustration of the paradigm along with two prototypical results: presence of GI for *integral dimensions*, documenting interaction in processing, and absence of GI for *separable dimensions*, documenting independence in processing with good selectivity of attention. This important distinction is elaborated in the Discussion [Figure 1]

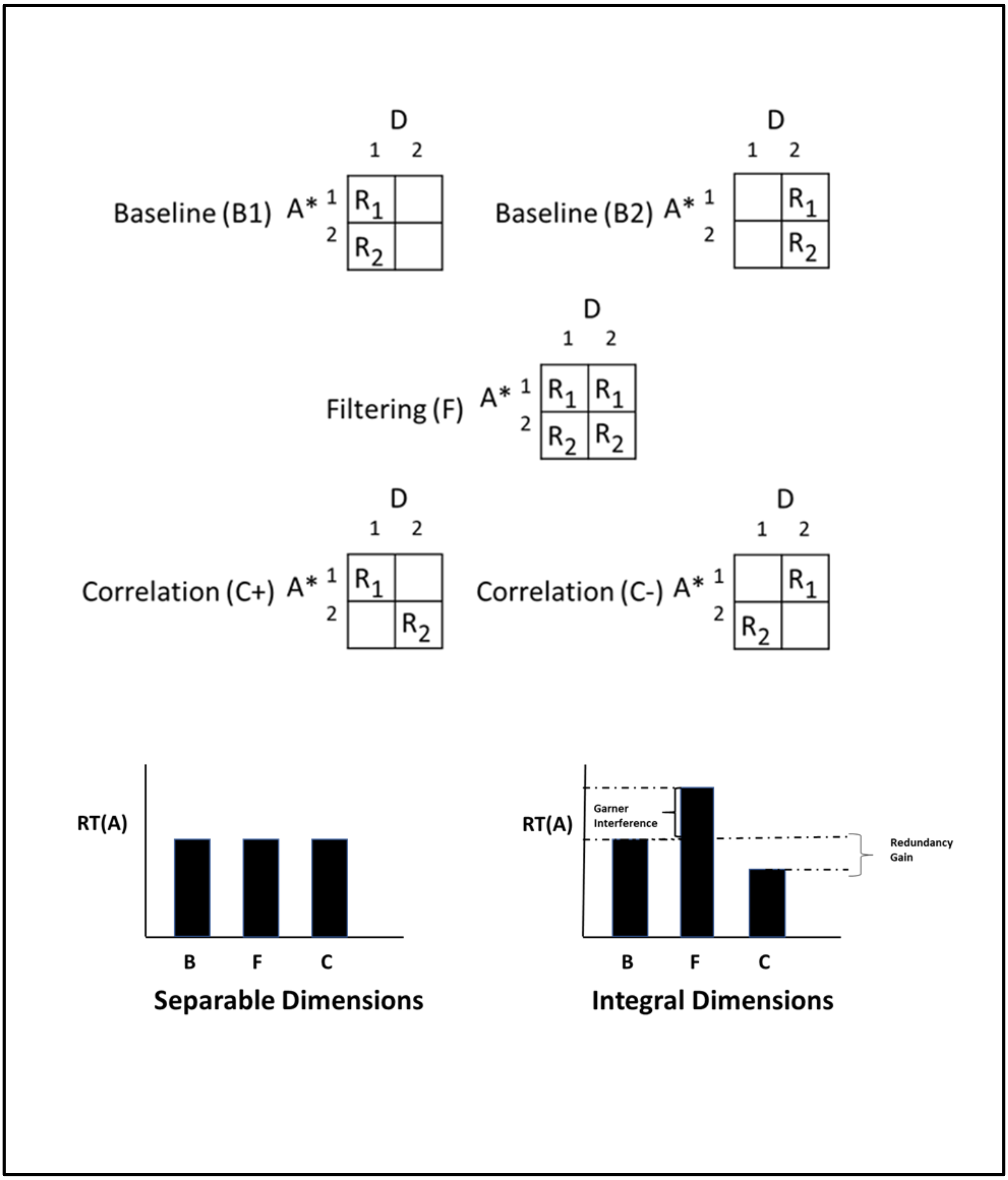

Figure 1: The Baseline, Filtering, and Correlation conditions of the Garner paradigm with two prototypical outcomes. Top: Baseline (with the irrelevant dimension D kept constant once at B1 and once at B2), Filtering, and Correlation (with two possible patterns of correlation) In all tasks, R1 and R2 are the correct responses to the vales A1 and A2 of the target dimension A (indicated by the asterisk). Bottom: The outcome with separable (left) and with integral (right) dimensions. The first difference depicted in the right-hand graph is Garner Interference. The second is Redundancy Gain wherein performance in Correlation is better than that in Baseline. Connecting to the example in the text, target dimension A is color, and irrelevant dimension D is shape. Values A1 and A2 are the colors red and green, whereas values B1 and B2 are the shapes triangle and circle.

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The Nature of Baseline

A glimpse at Figure 1 shows that performance is uniformly good at Baseline. What supports optimal performance in Baseline? According to the traditional explanation (e.g., Melara & Algom, 2003; Sabri, Melara & Algom, 2002; see also, Algom, Dekel, & Pansky, 1996; Burns, 2016; Melara & Mounts, 1993; Pomerantz, 1983), the fact that the irrelevant dimension is held at a constant value, namely, the absence of irrelevant variation, facilitates exclusive focusing on the target dimension. However, we posit that another possibility should also be considered, one entailing the concept of information rather than that of mere variation. Next, we develop the case for an information based GI and offer a new Garner condition for deciding between lack of variation vs. lack of information at B as the root cause of GI.

Information and Redundancy at Baseline

Because the irrelevant dimension is held at a constant value in Baseline, its value on trial n completely predicts the value on trial n+1. For example, if the irrelevant dimension of shape was fixed at the value of triangle in Baseline, then the triangle presented on trial n predicts that the same triangle also appears on trial n+1. Therefore, when a triangle appears on trial n+1 it conveys no novel i*nformation*. As far as the irrelevant dimension is concerned, at Baseline each trial (except the first) is completely redundant. We thus asked: Is Baseline performance good due to the absence of irrelevant variation, or is it good due to the fact that the irrelevant dimension is fully predictable (i.e., does not carry information)?

Let us elaborate a bit on the concept of information in the present context. Following the seminal work by Shannon (1948) and Wiener (1948), information theory has been informing psychological research to date (see Attneave, 1959, and Garner, 1962, for early reviews, and Fitousi, 2013, Laming, 2001, or Norwich, 1993, for more recent treatments). Suppose that an event can have many outcomes (e.g., the outcome of tossing a coin, the selection of one card from a shuffled deck of 52) and that the observer, quite naturally, is uncertain about the outcome. Then, information is defined as a reduction in that uncertainty when the outcome is revealed. At that point, uncertainty vanishes and information is gained. Therefore, information depends on the prior uncertainty of the outcome: The lower the prior probability of an outcome (hence, one is more uncertain about it), the more information is gained when it occurs. High probability events carry less information than do low probability events, and certain, fully predictable events, contain no information at all. Now, the outcome of each trial of the task-irrelevant dimension at Baseline is such a fully predictable predetermined event. Formally, following Shannon (1948), the information H of trial x is given by

$$H_x = -k \log_b p(x) \qquad k>0 \qquad (2)$$

where k is a constant and b is the base of the logarithm usually set to two in order to yield the "bit," the unit of information. It immediately follows that from a set of 1 outcome (i.e., with probability of 1.0), as is the case on each trial with the task-irrelevant dimension, information is zero,

$$H_x = -k \log 1 = 0 \text{ bits} \qquad (3)$$

The Baseline condition actually includes a sequence of trials. Given the invariance of the irrelevant condition, when the next trial occurs, the information it conveys is identical with information we have already received from the previous trials (re value of the irrelevant dimension). We call this repeated information "redundancy" (e.g., Miller, 1953). Let H_y stand for the information in the nth trial, and H_x for the (average) information of the preceding trials. Then, $H_x(y)$ can be thought of as the additional information gained on a trial when the information from the preceding trials is known. It is the amount of information in the nth trial that *cannot* be obtained from the previous trials. Clearly, $H_x(y)$ is zero on all trials at Baseline, meaning each trial is completely redundant and contains no additional information with respect to values of the task-irrelevant dimension

Obviously, the information contained in a stimulus is processed by the observer in order to generate the response: the larger the amount of information, the greater the processing load (e.g., Fitousi, 2013; Garner, 1962, 1970; Miller, 1953). The relation is neatly reflected in Hick's Law (Hick, 1952; Hellyer, 1963; Hyman, 1953; see also, Coren & Ward, 1989) stating that the time to react to a complex task is a linear function of the number of bits of information included in the task,

$$RT = cH \qquad c>1 \qquad (4)$$

where c is a constant.[1] In the Garner context, the fact that the task-irrelevant dimension is devoid of information, with consecutive trials being completely redundant, means that cognitive resources are not needed for its perception and processing. Consequently, all available resources are free to process the target dimension which is likely conductive to the good performance usually observed in the Baseline condition.

The question now arises: Is the good performance at Baseline due to lack information or due to lack of variation? The following new Garner condition may help in the decision.

The Roving Baseline Condition: Prying Apart Information and Variation

The classic Baseline task is not the only way to keep the values of the task-irrelevant dimension devoid of information. It is possible for those values to vary from trial-to-trial and yet to carry no information. Our new *Roving Baseline* task was created for that purpose. In this task, the values of the task-irrelevant dimension strictly alternate from trial-to-trial. For example, if the shape was a triangle on trial n, it is a circle on trial n+1, then again a triangle on trial n+2, followed by a circle on trial n+3, and so on. In this task, too, the value of the irrelevant dimension on trial n perfectly predicts the value on trial n+1, so that the outcome does not carry information. However, this zero information comes in the face of the presence of irrelevant variation.

Including the Roving Baseline condition in the experiment, one can pry apart the contributions of variance and information in generating the good performance at Baseline, and, consequently, in producing GI. Notably too, the Roving Baseline condition carries a further bonus: It contains the same number of stimulus combinations as does the Filtering condition. Following our color-shape example, both conditions entail 4 combinations: red triangle, red circle, green triangle, green circle. Each typical Baseline block, by contrast, entails only 2 stimulus combinations (e.g., red triangle and green triangle). This difference (sometimes referred to as a difference in stimulus uncertainty) poses a threat to the traditional account of Garner interference as the effect of irrelevant variation (e.g., Burns, 2016; Nosofsky & Palmeri, 1997).

Suppose that superior target performance in classic Baseline as compared to Filtering derives from the absence of irrelevant variation per se or from the reduced number of stimulus combinations. If so, performance in the new Roving Baseline condition should be poorer than that in classic Baseline -- due to the presence of irrelevant variation in the Roving condition. Under this hypothesis, performance in Roving Baseline should actually be comparable with that in Filtering because both conditions are marked by the presence of irrelevant variation that is uncorrelated with target variation and contain the same number of stimulus combinations (4). By contrast, if performance in Baseline derives from the lack of irrelevant *information*, the Roving Baseline condition should yield comparable performance to that in the classic Baseline condition (and better than that in Filtering). Note that this discussion and predictions pertains to macro or overall performance, i.e., mainly to RT averaged across all trials in each experimental condition. Can we reach a bit deeper in dissecting the unique features of each Garner condition?

Garner Micro Analyses: The Observer as Change Detector

Our focus in these fine grain analyses was the possible changes within two-trial strings in each condition. Consider the target dimension on trial n: it can repeat (R) or can change (C) with respect to its value on trial n-1. The same applies to the task-irrelevant dimension. Collectively, they produce 4 cases, RR, RC, CR, and CC, where the letters at the left and right refer to the target and irrelevant dimensions, respectively. This routine was pioneered by Felfody (1974), Huettel and Lockhead (1999), and Dyson and Quinlan (2010). However, consideration of the novel Roving Baseline condition invites further development that we present next. As we show, incorporating the Roving Baseline condition permits the examination of an interaction between the two possible sources of Garner interference.

The permissible two-trial sequences, or, more accurately, the content of trial n relative to its predecessor trial, n-1, in the various conditions are presented in Table 1. Included in Table 1 is our novel condition of Roving Baseline that differs from all the other classic and previously examined conditions. The main point to note is this. The Filtering condition entails all four possible two-trial types, whereas both the Baseline and the Roving Baseline conditions entail only two two-trial types. Furthermore, the two-trial types in Baseline and in Roving Baseline are disjoint.

Table 1: The possible values of the relevant and the irrelevant dimensions on trial n+1 as a function of their respective values on trial n for the three classical conditions of the Garner paradigm and for the new Roving Baseline condition.

	Baseline	**Roving Baseline**	Filtering	Correlation
RR	Yes	**No**	Yes	Yes
RC	No	**Yes**	Yes	No
CR	Yes	**No**	Yes	No
CC	No	**Yes**	Yes	Yes

Note: The left-hand letter in each doublet stands for the relevant dimension, the right-hand letter for the irrelevant dimension. The letter R stands for repetition of the dimensional value, and the letter C stands for a change of the dimensional value. For example, RR means that the value of the relevant dimension repeats on trial n and that the value of the irrelevant dimensions also repeats on trial n.

Considering only the traditional Baseline and Filtering tasks, Table 1 highlights the fact that irrelevant change trials, XC (with X standing for R or C), are included and measured in the Filtering condition alone. Observe also that irrelevant repetition trials, XR, are predetermined and hence carry no irrelevant information in Baseline, but the same irrelevant repetition trials in Filtering do carry irrelevant information – due to the fact that in that condition irrelevant change trials are also possible. This situation invites two informative contrasts. First, within Filtering, the difference between irrelevant change (XC) and irrelevant repetition (XR) trials isolates the effect of irrelevant change in the presence of irrelevant information.[2] Second, the difference between Filtering and Baseline with respect to irrelevant repetition (XR) trials isolates the effect of irrelevant information.

Next consider the Roving Baseline and Filtering tasks. When comparing them, one should be aware of the following two features. First, irrelevant repetition appears only in Filtering. Second, although irrelevant change appears in both conditions, it carries information only in Filtering (where the irrelevant dimension can remain the same or can change between trials). To isolate information, the difference in XC trials across Filtering and Roving Baseline specifies the effect of information carried by irrelevant change. Comparing Roving Baseline with the typical Baseline provides for a final valuable contrast. The difference between XC trials in Roving Baseline and XR trials in Baseline isolates the effect of irrelevant change in the absence of irrelevant information.

These intuitions prompted a formal decomposition, via two-trial strings, of Garner interference into the effects of *irrelevant change*, *irrelevant information*, and the *interaction* between these effects.   These effects are analogous to the effects that were considered at a more macroscopic level in the outset – again, with the proviso that they are based on two-trial sequences within each Garner condition. With this kept in mind, the main difference between the macro and micro analyses pertains to the definition of (irrelevant) variation and information: In the macro-analysis variation and information is interpreted as a property of the entire block (hence Filtering allows for irrelevant variation and contains information but Baseline does not), whereas in the microanalysis, one can distinguish between (irrelevant) variation and repetition (trials) within the Filtering condition. In Filtering, too, irrelevant values on all trials contain information because they could have been different than those presented in any particular trial. The upshot is, the two approaches provide complementary perspectives.

Formally, Equation 5 gives the effect of information for irrelevant repetition as follows,

$$\text{Information Effect for Irrelevant Repetition} = MRT(XR|F) - MRT(XR|B) \quad (5)$$

where X stands for R or C, F and B stand for Filtering and Baseline, respectively, and MRT is the mean reaction time for correct responses for all XR trials in each condition (i.e., the average of MRT(RR) and of MRT(CR)).[3] In Equation 5, the irrelevant dimension is fixed at R, but only in Filtering (but not in Baseline) it could have been C and hence it is informative. In a similar fashion we can measure the effect of information for irrelevant change, XC, as follows.

$$\text{Information Effect for Irrelevant Change} = MRT(XC|F) - MRT(XC|RB) \quad (6)$$

where RB stands for Roving Baseline. Then, the main effect for information is simply,

$$\text{Main Effect of Information} = [(5) + (6)]/2 \qquad (7)$$

The effect of irrelevant variation or change with or without informational value is derived as follows. First, the effect of irrelevant variation under the presence of information is given by Equation 8:

Irrelevant Variation in the Presence of Irrelevant Information = MRT(XC|F) – MRT(XR|F) (8)

Equation 8 partitions the Filtering condition strictly along the presence or absence of change in the irrelevant dimension. The effect of irrelevant variation in the absence of information is given by the difference between the two Baseline conditions as follows,

Irrelevant Variation in the Absence of Irrelevant information =MRT(XC|RB) – MRT(XR|B) (9)

Then, the main effect of irrelevant variation is,

Main Effect of Irrelevant Variation = [(8) + (9)]/2 (10)

Finally, the two main effects are conveniently incorporated into a 2x2 ANOVA as depicted in Figure 2. Without the Roving Baseline condition, one cannot establish Equations 7 and 10, and, as a result, one cannot not derive the interaction of the two main possible sources of Garner interference. When inspecting Figure 2 it is important to keep in mind that the current analyses and effects are based on and limited to two-trial sequences. Consider for example the entry at the upper right: It is defined by the *absence* of irrelevant change and the *presence* of information. Consequently, the entry specifies that subset of two-trial sequences within Filtering where the irrelevant dimension did not change between trials n-1 and n. These trials simultaneously carry irrelevant information due to the fact that the irrelevant dimension *could have changed* between trials n-1 and n, although it did not.

		Irrelevant Information	
		Absent	Present
Irrelevant Variation	Absent (Repetition)	Baseline	Filtering repetition
	Present (Change)	Roving Baseline	Filtering change

Figure 2: Four types of *two-trial sequences* created by the factorial combination of variation along the irrelevant dimension (present, absent) and information carried by the values of the irrelevant dimension (present, absent). The four types of trials fall into the four combinations (clockwise from upper left): Baseline (XR), Filtering trials in which the value of the irrelevant dimension repeats (XR), Filtering trials in which the value of the irrelevant dimension changes (XC), and Roving Baseline (XC).

Empirical Exploration

Our goal was to follow performance in the novel Roving Baseline condition in the context of both separable and integral dimensions. We thus selected prototypical pairs of dimensions for each type (see Algom & Fitousi, 2016, for a list of dimensions documented in the literature for each type). For the separable case, the dimensions were tilt of diameter and size of circle (with tilt as the target dimension); for the integral case, the dimensions were height and width of a rectangle (with height as the target dimension). To anticipate, the values chosen for the target dimension of tilt in the separable case turned out to be very difficult for discrimination; hence, unlike the usual pattern, these dimensions, too, yielded Garner Interference. We note that, in their classic study, Garner and Felfoldy (1970) have already shown that when separable dimensions mismatch in salience, they, too, produce Garner Interference. We hasten to add that the resulted pattern in no way compromises the validity of all of our analyses and observations.

Therefore, in two experiments the participants performed in three conditions of the Garner paradigm: Baseline, Roving Baseline, and Filtering. In Experiment 1, the participants decided, while timed, the angle of a diameter crossing a circle (steep, moderate), while ignoring circle size (large, small). In Experiment 2, the participants decided the height of a rectangle (long, short), while ignoring its width (wide, narrow).

Experiment 1

Method

Participants: Thirteen Tel-Aviv university students (9 women) participated in Experiment 1 in partial fulfillment of course requirements. All participants had normal or corrected-to-normal vision.

Stimuli and Apparatus: The stimuli were circles crossed by a diameter, presented in black outline over a white screen. The thickness of the circles and their diameters was 0.794 mm. The circles could be small (with a diameter of 4.5 cm) or large (with a diameter of 9 cm) in size, and the tilts of the diameters could be moderate (4°) or steep (7°). The experiment was conducted on an HP Compaq 6000 Pro MT computer. Stimulus presentation and the measurement of time were governed by DirectRT Precision Time Software (Version v2014.1.104). The stimuli were displayed on a LG L1953HM monitor set to resolution of 1280X1024 pixels.

Design: From the four possible stimulus combinations – a large circle crossed by a diameter of moderate tilt, a large circle crossed by a diameter of steep tilt, a small circle crossed by a diameter of moderate tilt, and a small circle crossed by a diameter of steep tilt -- we created the three experimental tasks of Baseline, Roving Baseline and Filtering. The relevant dimension for responding in all tasks was the steepness of the diameter. The tasks are described below.

Baseline: This condition consisted of two blocks with the irrelevant circle held constant at small size in one block and at large size in the other block. Each Baseline block included 24 trials.

Roving Baseline: In this condition, the irrelevant circle strictly alternated in size from trial-to-trial. If a small circle was presented on trial n, a large circle followed on trial n+1 and these oscillations continued throughout the block. This condition included 48 trials.

Filtering: In this condition, both the relevant tilt and the irrelevant circle varied from trial-to-trial in a random fashion. This condition included 48 trials.

The order of the three conditions, Baseline, Roving Baseline, and Filtering, was random and different for each participant (subject to the proviso that the two blocks within Baseline were presented in succession but in a random order between the two).

Procedure: The participants were tested individually. The participant was sitting approximately 60 cm from the monitor. To avoid adaptation and other unwanted effects, we introduced a trial-to-trial spatial uncertainty of 34 pixels around the center location. The stimulus remained visible until the participant's response. The four blocks were separated from each other by half-a-minute breaks. In the beginning of the experiment, the instructions and the stimuli were presented to the participants. The participants were asked to respond to the slope of the diameter as fast and accurately as possible by pressing one of two lateralized keys.

Data Analysis: Error rates were high with 18.3% in Baseline, 18.4% in Roving Baseline, and 21% in Filtering. The conditions did not differ in error rate ($F<1$). Given the within-subject design and the absence of a difference in error rate, we calculated the correlation across the individual participants between overall mean RT and overall error. Despite the high error rates, there was not a speed-accuracy tradeoff [$r(11) = -.002$]. The high error rates observed reflected the extreme difficulty of the diameter task. The angles in this experiment were very hard to distinguish. The current values of difference in orientation were 10 times smaller than those used in the study by Potts, Melara, and Marks (1994), and over 5 times smaller the values used in the study by Felfoldy, 1974). The analyses entail correct responses only.

Results

Figure 3 presents the results. Shown are the mean correct RTs for the three conditions of Baseline, Roving Baseline, and Filtering. The mean RTs were 860, 1002, and 996 ms, in Baseline, Roving Baseline, and in Filtering, respectively, [F (2,

24) = 13.2, p < .001, η^2_p= .523; repeated-measures ANOVA]. Notably, performance in Baseline differed from that in the Roving Baseline (p < 0.002) and from that in Filtering (p < .007), but performance in Roving Baseline and in Filtering did not differ from each other (p>>.10). Therefore, we recorded an appreciable Garner Interference of 136 ms with respect to the traditional Baseline, but none with respect to the novel Roving Baseline.

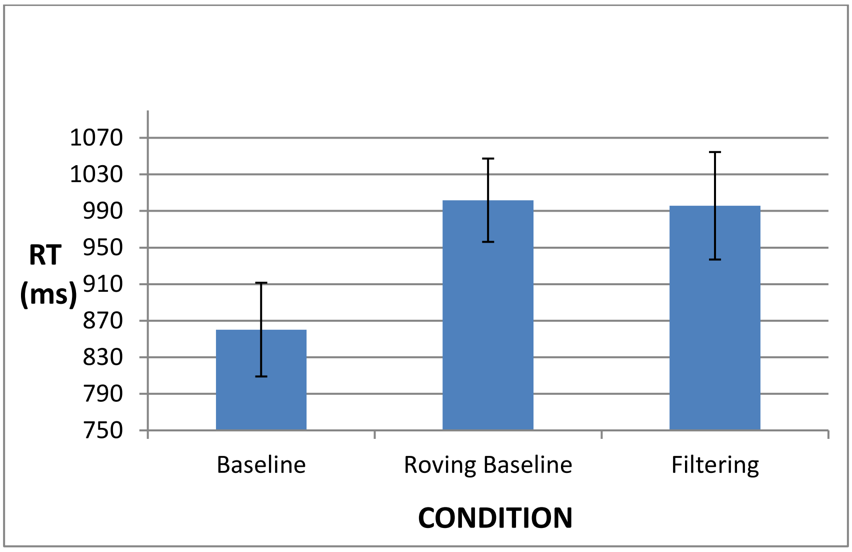

Figure 3: Mean correct RTs for tilt classification in three Garner conditions. The bars denote one standard error around the mean.

Apparent in Figure 3 is the difference in classification performance across conditions. Most important for the present purpose is the appreciable difference between the two Baseline conditions. Our participants responded to the target dimension of orientation faster in the typical Baseline than in the roving Baseline. Performance in Roving Baseline condition was sluggish, and was in fact comparable with that in Filtering. These results suggest that Baseline performance is good mainly due to the absence of irrelevant variation or due to the fact that there are only 2 different stimuli and not due to the absence of irrelevant information. Even with perfect predictability along the task-irrelevant dimension in Roving Baseline, the mere presence of change impaired performance to make it as worse as that in Filtering.

We next consider the results of the micro-analysis. Table 2 provides the results of speed of responding for the various two-trial sequences included in the three conditions of Baseline, Roving Baseline, and Filtering.

Table 2: Mean RTs (in ms) on trial n with respect to trial n-1 for possible two-trial sequences in three Garner conditions

	Baseline		Roving Baseline		Filtering	
	RR	879	RC	1028	RR	899
	CR	845	CC	997	CR	932
					RC	1053
					CC	1028
Marginal Mean		862		1012.5		978

Note: The marginal means per Garner block in Table 2 differ slightly from the means in Figure 2 due to the different route employed. Here we first calculated the means per stimulus type, then averages across types.

In Figure 4, we arranged the results of the two-trial sequences (shown in Table 2) according to the two main variables, both referring to the irrelevant dimension: Change or Variation (present, absent) and Information (present, absent). The ANOVA revealed a highly significant main effect of irrelevant variation [$F(1,12) = 19.34$, $p<.01$, $\eta^2_p= .648$)], but no effect of information [$F(1,12) = 3.22$, $p>.05$)]. Notably, these two main factors did not interact ($F<1$). [Figure 3]

		Irrelevant Information	
		Absent	Present
Irrelevant Variation	Absent (Repetition)	Baseline 862	Filtering Repetition 916
	Present (Change)	Roving Baseline 1012	Filtering change 1040

Figure 4: As in Figure 2, for the results of Experiment 1. Variation and Information refer to the value of the irrelevant dimension on trial n with respect to its value on trial n-1. Mean RT (in ms) appear in each entry.

The global outcome with respect to the three conditions (Figure 3) and the results of the microanalysis (Table 2 and Figure 4) converge on the same conclusion: Good Baseline performance, hence GI, is largely produced by the presence of irrelevant variation in Filtering and its absence in Baseline. We found no evidence for an effect of irrelevant information.

Experiment 2

Method

Participants: Seventeen participants (12 women), all Tel-Aviv University undergraduate students, participated in partial fulfillment of course requirements. All participants had normal or corrected-to-normal vision.

Stimuli and Apparatus: The stimuli were rectangles presented in black outline in the center of the monitor on a white background. The rectangle’s width could be 3.5 cm (wide) or 3 cm (narrow); the height could be 3.5 cm (short) or 5.5 cm(long). All other details were the same as in Experiment 1.

Design: The design was the same as that of Experiment 1. The Baseline condition included 48 trials, and the Roving Baseline and Filtering conditions included 96 trials each.

Procedure: In all three conditions, the participant responded to the height (short, long) of the presented rectangle by pressing the appropriate lateralized key.

Data Analysis: Mean error rate was 9% in Baseline and it was 10% in both Roving Baseline and Filtering. Again, error rates did not differ across conditions. And, again, we did not find a speed-accuracy tradeoff [$r(15) = -.133$]. The analyses concern correct RTs only.

Results

Figure 5 depicts the mean (correct) performance in each condition. The mean RTs were 534, 598, and 590 ms, in Baseline, Roving Baseline, and Filtering, respectively [$F(2,32) = 8.372$, $p = .001$, $\eta^2_p = .344$]. Again, the most important feature of the data is the difference between the two Baseline conditions ($p < 0.002$). And, again, the mean RT in Filtering was significantly greater than that in Baseline ($p<.05$), but no difference was found between the Roving Baseline and the Filtering conditions. These results replicate those of Experiment 1 with another pair of dimensions. We recorded an appreciable Garner Interference of 56 ms with respect to the usual Baseline condition, but none with respect to the Roving Baseline condition. The absence of irrelevant variation at Baseline seems to be the main (sole?) factor[4] responsible for the optimal target performance and, indirectly, for Garner Interference.

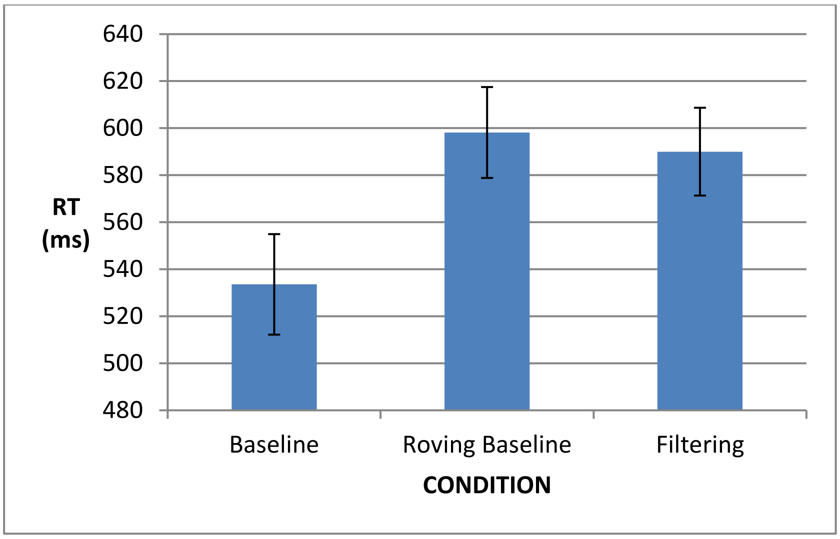

Figure 5: Mean correct RTs for classification of the height of rectangles in three Garner conditions. The bars denote one standard error around the mean.

We next report the results of the microanalyses. The mean RTs for the various two-trial sequences in the three conditions of Baseline, Roving Baseline, and Filtering appear in Table 3.

Table 3: Mean RTs (in ms) on trial n with respect to trial n-1 for possible two-trial sequences in three Garner conditions

	Baseline		Roving Baseline		Filtering	
	RR	519	RC	595	RR	530
	CR	547	CC	605	CR	610
					RC	620
					CC	608
Marginal Mean		533		600		592

In Figure 5, we again arranged the results of the two-trial sequences (shown in Table 3) according to the status of the irrelevant dimension: Change or Variation (present, absent) and Information (present, absent). The ANOVA revealed a highly significant main effect of irrelevant variation [$F(1,16) = 52.7$, $p<.0001$, $\eta^2_p = .767$)], but a statistically insignificant effect of irrelevant information [$F(1,16) = 2.45$, $p>.05$)]. The two main factors did not interact ($F<1$).

		Irrelevant Information: Absent	Irrelevant Information: Present
Irrelevant Variation	Absent (Repetition)	Baseline 533	Filtering Repetition 570
	Present (Change)	Roving Baseline 600	Filtering change 614

Figure 6: As in Figures 2 and 4 for the results of Experiment 2.

In sum, the overall results of Experiment 2 join those of Experiment 1, implicating irrelevant variance – absent in Baseline, present in Filtering -- as the major source of Garner interference.

Discussion

The structure of the Discussion is as follows. First, we review the results with respect to the three possible sources of Garner Interference examined – variation, information, and stimulus uncertainty. Our discussion is informed by pairwise contrasts of the different sources. Subsequently, we discuss 5 foundational issues in the Garner domain: (1) the Integrality-Separability distinction, (2) the role and diagnostic value of the Correlation condition, (3) the role of Configural processing as a source of Garner Interference, (4) the role of a change detection strategy as a source of Garner interference, and (5) the virtues and limitations of micro- and macro-analyses. We conclude by vindicating Garner’s original intuition on the predominance of irrelevant variation.

Three Sources of Garner Interference

There are three key differences between Filtering and Baseline in the standard Garner paradigm: (a) irrelevant variation, (b) irrelevant information, and (c) stimulus uncertainty or number of stimuli. Each of these differences can account for the relatively poor performance in Filtering, and, as a result, for Garner Interference. Traditional interpretations implicate the first difference as the root cause of Garner Interference. Because irrelevant variation is allowed only in Filtering, it is its presence that most readily explains the detriment in performance called Garner Interference (e.g., Algom, 2016; Algom et al., 1996; Algom & Fitousi, 2016; Algom, Fitousi, & Eidels, 2017; Amishav & Kimchi, 2010; Eidels, Townsend, & Algom, 2010; Garner, 1970, 1974, 1976; Pomerantz, 2983). In contrast, several authors of formal models of Garner Interference pinpoint the third difference, the greater number of stimuli, as the cause of the slowdown in Filtering (e.g., Ashby & Maddox, 1994; Fific, Nosofsky, & Townsend, 2008; Nosofsky & Palmeri, 1997; see also Burns, 2014, 2016). In the present work, we suggested yet another possibility – the difference in information content. Due to the constant value of the irrelevant dimension at Baseline, it conveys no information. As a result, all cognitive resources in this condition can be deployed to the single varying dimension, the target dimension. The need to process (more) information in Filtering is conductive to the slowdown observed in that condition. Which explanation of the three, if any, is supported by the data at hand? To weigh the evidence, we next compare each alternative against the benchmark theory of irrelevant variation.

Irrelevant Variation vs Irrelevant Information

In this study we highlighted the trivial fact that the value of the task-irrelevant dimension at Baseline is completely predictable from trial-to-trial. The observer may ignore the irrelevant dimension not because it is held constant but because it is not informative. However, perfect intra-dimensional predictability does not mandate a constant value. The values of the task-irrelevant dimension can change and yet be fully predictable from one trial to the next. This idea was embodied in our new Roving Baseline condition. In the Roving Baseline condition, the value of the irrelevant dimension on trial n was completely determined by its value on trial n-1 (as is the case in Baseline), but the values varied from trial to trial (as they do in Filtering). The results showed that the mere presence of irrelevant variation, however predictable, proved fatal for the selectivity of attention. Introducing a predictable periodical change in the Roving Baseline condition still led to the breakdown of selectivity -- to the same extent as did the presence of irrelevant variation in Filtering. As a result, Garner Interference was present and was comparable in Filtering and in Roving Baseline. Notice that the irrelevant dimension carries the same amount of information in Baseline and in Roving Baseline (zero bits), and yet performance is worse in Roving Baseline likely due to the presence of irrelevant variation. Notice too that Filtering entails more irrelevant (dimension) information content than Roving Baseline, but again this imbalance in information does not make a difference in performance -- due likely to the presence of irrelevant variation in the two conditions. In sum, we have no evidence that irrelevant information affects performance.

The results of the microanalyses in both experiments reveal large and significant effects of irrelevant change or variation, but very small insignificant effects of irrelevant information. Further in this respect, consider the contrast within Filtering between trials in which the value of the irrelevant dimension changes (XC) and those in which it repeats (XR). Because these sequences are drawn from the same condition (i.e., with information constant), the large difference in performance favoring XR indicates that it is irrelevant change that generates the slowdown. In sum, we found no evidence supporting irrelevant information as a (major) source of Garner Interference.

Irrelevant Variation vs Stimulus Uncertainty

Stimulus uncertainty poses the major threat to the traditional explanation of Garner Interference in terms of irrelevant variation. Filtering differs from Baseline not only in the presence of variation along the irrelevant dimension, but also in greater stimulus uncertainty (4 stimuli in Filtering vs. 2 in Baseline). The slowdown observed in Filtering can derive from the presence of irrelevant variation *or* from the greater number of stimuli. Is there evidence in the current data to implicate irrelevant variation as a contributor to the interference? We believe there is. Indeed, the aforementioned difference within Filtering between XC and XR trials favoring the latter, directly implicates irrelevant variation (Dylan & Quinlan, 2010). Because the two types of trials come from the same condition, stimulus uncertainty is ruled out as an explanation.

Recently, Burns (2014, 2016) demonstrated via another ingenious route that irrelevant variation is a determining factor of Garner Interference (above and beyond possible contribution of the number of stimuli). Burns conceived a new condition, *Correlated Filtering*, which includes *two* irrelevant dimensions. Notably, the pair of irrelevant dimensions vary in tandem (hence Correlated), but in a random fashion with respect to the task-relevant dimension (hence Filtering). The most important point to note is that the number of stimuli is the same in Filtering and in Correlated Filtering (e.g., if there are 4 stimuli in Filtering, there are 4 stimuli in Correlated Filtering), but that there is an added dimension of variation in Correlated Filtering. To illustrate the new condition, consider our Experiment 2 with the rectangle stimuli.

In Filtering our participants classified height as short or long (the target dimension) while attempting to ignore width that also varied randomly from trial to trial between short and long (the irrelevant dimension). Now suppose that we added another irrelevant dimension, color, so that when irrelevant width is short it appears in red, and when it is long it appears in green. The irrelevant dimension of color thus is correlated with the irrelevant dimension of width. Let us underscore again that stimulus uncertainty is the same in Filtering and in Correlated Filtering. Burns found that that Garner interference was larger in Correlated Filtering than in Filtering, and concluded that stimulus uncertainty cannot (solely) explain Garner Interference.

In sum, the present data and conclusions concur with those of other investigators, implicating irrelevant variation as a major causal source driving Garner Interference. We must discuss 5 foundational issues before concluding.

Five Foundational Issues in the Garner Realm

The Integrality-Separability Distinction and Stimulus Uncertainty

The prevalence of perceptually separable pairs of dimensions arguably provides the most powerful evidence against an effect of stimulus uncertainty in the Garner domain. As a rule, separable dimensions (e.g., color and shape) do not produce Garner Interference -- performance is the same in Baseline and Filtering -- despite the change in the number of stimuli. In fact, Garner Interference serves as a powerful diagnostic in this respect (absent with separable dimensions, present with integral dimensions). Now, as Burns (2016) astutely observes, if Garner Interference were caused simply by the number of stimuli, its presence would tell us little about the nature of the dimensions. The integrality-separability distinction itself, a pillar of cognitive science, would collapse, with grave implications for large swathes of cognitive psychology. Given the impact of the distinction over the last five decades (Algom & Fitousi, 2016), entire areas would then be revisited. Clearly, that is not the case. Available evidence militates against the possibility of a significant role of stimulus uncertainty in Garner domain.

Again, a word is in order with respect to the dimensions used in current Experiment 1, circle size and tilt of the diameter. These are prototypical separable dimensions, with neither dimension usually intruding on performance with the other, so that they produce no Garner Interference (Garner, 1974; Garner & Feloldy, 1970). In contrast, we recorded Garner Interference with these dimensions in our Experiment 1. The reason is that circle size, the task-irrelevant dimension, was much more salient or discriminable than the target dimension of diameter tilt. When the dimensions are (substantially) mismatched in discriminability, then the more discriminable dimension intrudes on the less discriminable dimension. This effect of mismatched discriminability was first demonstrated by Garner and Felfoldy (1970) and has since been replicated and expanded numerous times (e.g., Algom et al., 1996; Fitousi & Algom, 2018; Melara & Algom, 2003; Melara & Mounts, 1993, 1994; Pomerantz, 1983; Sabri, Melara, & Algom, 2002).

The Correlation Condition of the Garner Paradigm

Our focus in this study was the nature of the Baseline condition, in particular the way it generates Garner Interference. As a result, we tested the two Baseline conditions and Filtering -- their difference providing the measure of Garner Interference. However, as shown in Figure 1 and in Table 1, the paradigm often includes a third condition, Correlation. In Correlation, the task-relevant and the task-irrelevant dimensions vary in tandem. Given the dimensions of color and shape with color as the to-be-responded dimension, on all trials when the target color is red the irrelevant shape is a triangle, and on all of the remaining trials when the color is green the shape is square. In the complementary Correlation block, the association reverses: When the color is red it fills a square, and when it is green it fills a triangle (see Figure 1 again).

Now, there is a surprising similarity between Correlation and the novel Roving Baseline. Unlike Baseline, in which the irrelevant dimension is held constant, in both Correlation and Roving Baseline the task-irrelevant dimension varies from trial-to-trial. However, the similarity stops at this point. In Roving Baseline, the sequence of values of the irrelevant dimension is completely predictable. The value on trial n-1 determines the value on trial n.[5] In sharp contrast, in Correlation, the sequence of values on the *irrelevant dimension* is random. The value on trial n-1 does not predict the value on trial n. Another difference is consequential. In Roving Baseline, the target and the irrelevant dimensions vary in a completely independent fashion with zero correlation between the two. In Correlation, by contrast, the two dimensions vary in tandem with perfect correlation between their values across all trials.

These differences explain the disparate outcomes obtained with the two conditions. Performance in the Correlation condition is usually *superior* to that at Baseline, the difference called Redundancy Gain (see Figure 1, bottom right, again). In contrast, performance in the Roving Baseline condition is *worse* than that in Baseline (see Figures 3 and 5). The key for understanding the source of the difference is the nature of irrelevant variation. The presence of irrelevant variation is a necessary condition for Garner Inference to emerge, as we just documented in the current study. However, the Correlation condition also reveals that the irrelevant variation must be independent of the variation of the target dimension for Garner Interference to emerge.

Let us take a brief look at the notion of Redundancy Gain. Because the two dimensions are perfectly linked under Correlation, either the target dimension or the nominally irrelevant dimension is sufficient to determine the response. The observer is actually afforded with two signals for producing the response, an advantage conductive to superior performance (as captured by Redundancy Gain). Now, Redundancy Gain is considered an indicator of integral dimensions (in addition to the main marker of Garner Interference), but it is a dubious diagnostic indeed. To understand, consider the mathematically sustained principle of the Redundant Target Effect (RTE): Reaction times are faster for simultaneously presented targets than for each target presented alone -- even though each target is sufficient for producing the response on its own. Notably, the RTE is also present when the targets are completely independent, the gain known as statistical facilitation (e.g., Raab, 1962; Miller, 1978, 1982; Townsend & Nozawa, 1995, 1997; see also, Algom et al., 2015; Fitousi & Algom, 2018). So, in the realm of Garner, Redundancy Gain is eminently possible, even expected, for separable dimensions as much as it is for integral dimensions (e.g., Ashby & Townsend, 1986; Ashby & Maddox, 1994; Maddox & Ashby, 1996; Nosofsky & Palmeri, 1997; see also, Algom et al., 2015; Burns, 2014, 2016; Eidels, 2012; Eidels, et al., 2010). Although its size can be larger for integral than for separable dimensions, it is moot whether Redundancy Gain is a dependable indicator of integrality.

Garner Interference as a Marker of Gestalt or Configural Processing – Sometimes

The stimuli in the Garner experiment are compounds of dimensional values. The pairs of values sometimes generate distinct Gestalts due to emergent features that each combination entails. In such cases, performance is determined by the various Gestalts, rather than by the underlying dimensions. The classic study of such Gestalts and the attendant configural processing is that by Pomerantz and Garner (1973). The 4 stimuli of the Garner paradigm in that study are presented in Figure 7.

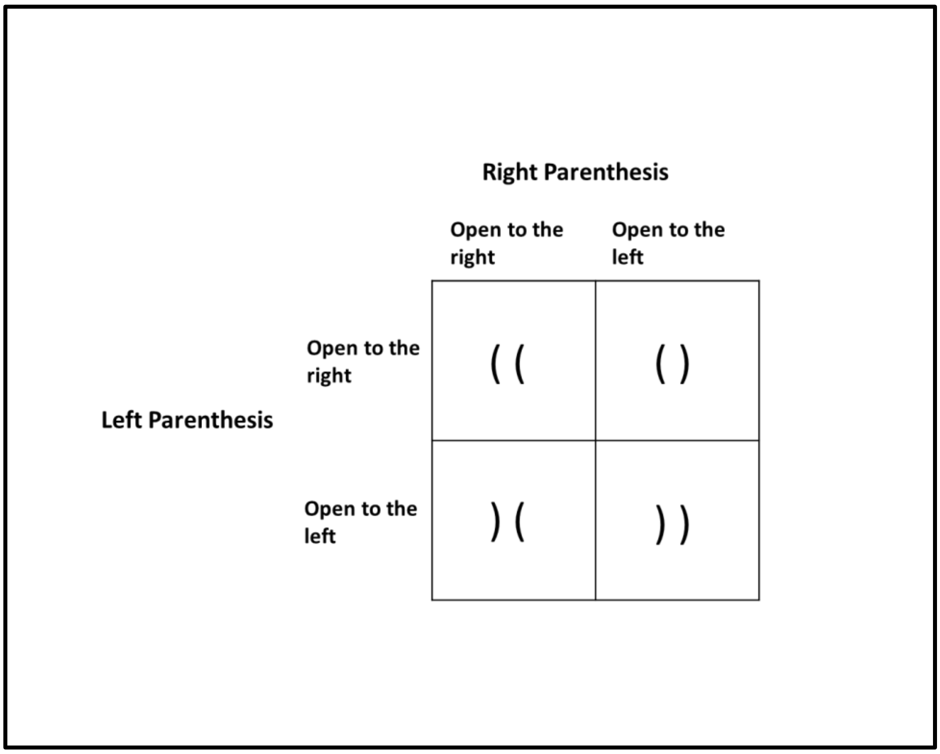

Figure 7: Illustration of the stimuli presented in the study of Pomerantz and Garner (1973). The dimensions are Left and Right parenthesis, each with opening to the left or opening to the right. Notice the unique Gestalts produced by the conjoined dimensional values via emergent features such as symmetry, parallelism, or closure.

In Figure 7, the two dimensions are (A) Orientation of the Left-Hand Parenthesis (left vs right) and (B) Orientation of the Right-Hand Parenthesis (left vs right). Suppose that the relevant dimension for responding is Dimension B, i.e., the task is to decide the orientation of the right-hand parenthesis. Thus, in one Baseline task, the two stimuli are ((and (), the first row of the matrix in Figure 7. Given the emergent features contained in these pairs – symmetry, parallelism, closure – the participant presumably attends to each pair as a whole in order to reap the gain to performance afforded by these Gestalt principles. Pomerantz and Garner (1973) found that performance at Baseline was indeed speedy and accurate. Further, as Pomerantz and Garner (1973) observed, the participants exhibited large amounts of Garner Interference. However, the latter did not implicate a failure to attend selectively to the right- or to the left-hand parenthesis; rather, the presence of Garner Interference reflected the participants' propensity to process each stimulus at Baseline as a unified whole (in Filtering the emergent features are less serviceable for responding). In these cases, Garner Interference is better thought of as an improvement at Baseline rather than as a detriment in Filtering.

In scrupulous and persuasive research spanning the course of over three decades, James Pomerantz succeeded in identifying an exhaustive list of emergent features, each with its attendant configural superiority effect (e.g., Costa, …Pomerantz, et al., 2018; Pomerantz, 1983, 1991, 2003, 2006; Pomerantz & Pristach, 1989; Pomerantz, Pristach, & Carson, 1989; Pomerantz, Sager, & Stoever, 1977). Pomerantz demonstrated that configural processing can be quite common in determining the outcome in the Garner paradigm.

This much granted, one should note that mere appearance of a Gestalt is insufficient for configural processing to occur. The Gestalts must also be *distinct* from one another, a stipulation that is not satisfied in many Garner studies. Consider the stimuli in current Experiment 1 – a circle crossed by a diameter, with the diameter's tilt as the target dimension. Now, a circle crossed by a straight line arguably forms a good Gestalt. However, our two stimuli at Baseline differed only by a very small (hardly perceptible) degree of the orientation of the line. So, if one of the stimuli forms a Gestalt, it is the same Gestalt in the other, meaning that processing cannot be based on emergent features.

The present results with respect to the Roving Baseline condition also pose a problem for the configural processing account. The typical Baseline condition and the Roving Baseline condition entail exactly the same Gestalts, yet only the former yields configural superiority, also known as Garner Interference.

Change Detection: Yet Another Strategy of Gestalt Processing in Baseline

A somewhat similar challenge to explanation in terms of irrelevant variability is a response strategy based on holistic stimulus processing at Baseline. In Baseline, the participant can use a *change detection* strategy, so that the response repeats or changes based solely upon whether the stimulus as a whole repeated or changed. Complete stimulus repetition mandates response repetition in Filtering, too. However, stimulus *change* in Filtering can mean either response repetition (in RC trials) or response switch (in CR and CC trials). As a result, detecting a change in the stimulus in Filtering stipulates analytic processing to disambiguate the stimulus and deciding on the response -- slowing down performance. According to this explanation, too, Garner Interference may reflect an improvement at Baseline, rather than a detriment in Filtering. In both of our experiments, performance was comparable for RR trials across Baseline and Filtering, but CR trials were slower in the latter condition. In fact, RC trials were the most difficult ones in Filtering, reflecting the ambiguity of stimulus change in regard to the required response. These results are consistent with the spirit of an explanation in terms change detection at Baseline. We also note that our novel

Roving Baseline condition excludes full stimulus repetition and hence does not allow for adopting a holistic change detection strategy. This might explain why performance in Roving Baseline was slower than in Baseline.

Nevertheless, we believe that change detection strategy does not offer a full account of Garner's Interference. In Experiment 1, CC trials were slower than CR trials in Filtering. Because both types entail a stimulus change, the difference suggests the presence of interference due to irrelevant change. In Experiment 2, by contrast, CC and CR trials yielded comparable performance, leaving open the possibility of an effect due to change detection strategy. Future studies could address the issue by conceiving novel designs that exclude stimulus repetition in all conditions. For example, in a 3 X 3 (rather than 2 X 2) stimulus design, one could create the Baseline, Filtering, and Roving Baseline conditions such that the relevant dimension never repeats from one trial to the next.

Efficacy and Limitations of Micro Analysis

Finally, some of the present conclusions were based on micro analyses, so that a word seems in order for evaluating this routine. Micro analyses, in particular examination of two-trial sequences, are increasingly popular in speeded tasks. For example, in the allied task of Stroop (Stroop, 1935), the currently popular notions of conflict monitoring and control are based on such analyses (e.g., Botvinick et al., 2001; Gratton, Coles, & Donchin, 1992; but see, Algom & Chajut, 2019). In the Garner realm, Feldoldy (1974) in his pioneering study, Huettel and Lockhead (1999) and more recently and fully Dyson and Quinlan (2010) have attempted this routine. These analyses have contributed to our understanding of the underlying processes especially as they measure local influences through sequential effects that are missed in the standard macro analysis. Their contributions granted, in the Garner domain in particular, micro analyses have a structural limitation. The hallmark of the Garner paradigm is the *overall* regime or atmosphere imposed on the experimental block. The participant perceives -- over the trials in the block -- that there is no irrelevant variation, that there is random variation of a distractor, or that there is irrelevant variation but one that is correlated with the target. Analysis via encapsulated stimuli misses the totality of the regime imposed on the block, the regime that defines the block and separates it from the other blocks.

In support of this limitation, Burns (2016) found slower responding in Correlated Filtering as compared with Filtering even when examining only XR trials, i.e., trials in which the irrelevant dimension(s) repeated. Recall that stimulus uncertainty is matched in Filtering and Correlated-Filtering and hence cannot account for this difference. Instead, this contrast suggests that the “extra” irrelevant variation in Correlated Filtering imposes a block-wide context, taxing response speed even on trials when such variation do not to occur. In sum, macro and micro analyses complement one another in providing information on different facets of processing.

Conclusion

Wendell R. Garner was acutely aware of the indeterminacy regarding the interference that has subsequently become to bear his name (for example, see the section titled, "What causes interference?" in Garner, 1974, pp. 139-140). After considering the available evidence, Garner inclined toward implicating irrelevant variation as the major source of the interference. Our analysis and data bear out Garner's intuition. Surely, various confounds pose a threat to the original interpretation of the breakdown of selectivity by the presence of irrelevant variation. However, when all evidence is considered it is irrelevant variation that most likely generates Garner interference.

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Footnotes

1. Note that H in Equation 4 is related to the concept of entropy (not strictly to a trial as in Equation 2).
2. The contrast between XC to XR can be further subdivided into its two component contrasts with predictions made based on a change detection strategy along with the need to disambiguate the stimulus for deciding the response (please consult the Discussion on change detection strategy). Thus, the component RC-RR should be positive with RR the fastest of all. This was found to be the case in both of our experiments (see Tables 2-3). Conversely, the component CC-CR should be negative

with CR the slowest of the 4 pairings. This prediction is inconsistent with the data: The contrast was not negative and CR was not the slowest stimulus in both experiments.

3. As we state in the main text, this difference might incorporate a potential effect of stimulus uncertainty.

4. What complicates a resolution is that the absence of variation is confounded with stimulus uncertainty. With only two stimuli at Baseline (as is the case in the standard Garner paradigm), the observer may well adopt a change detection strategy in that condition, speeding up performance. The problem granted, Burns (2016) does suggest that variability is a (major) factor at the least in the generation of Garner Interference.

5. In the Roving Baseline condition, the value of the irrelevant dimension on trial n-1 determines its value on trial n. On a first glance, this regime might seem some kindred of the "n-back" task in working memory wherein the stimulus on trial n is predicted by, say, trial n-4. The "n-back" task is notoriously difficult. In contrast, the strictly alternating current regime does not tax memory. Observers are not asked to attend to the sequence or made cognizant of its presence or form. Moreover, the sequence occurs in the task-irrelevant dimension that observers might well ignore.

Open Practices Statement: The data and materials of both experiments are available upon request from the first author

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