

The Relative Success of Recognition-Based Inference in Multichoice Decisions

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Abstract

The utility of an “ecologically rational” recognition-based decision rule in multichoice decision problems is analyzed, varying the type of judgment required (greater or lesser). The maximum size and range of a counterintuitive advantage associated with recognition-based judgment (the “less-is-more effect”) is identified for a range of cue validity values. Greater ranges of the less-is-more effect occur when participants are asked which is the greatest of m choices ($m > 2$) than which is the least. Less-is-more effects also have greater range for larger values of m . This implies that the classic two-alternative forced choice task, as studied by Goldstein and Gigerenzer (2002), may not be the most appropriate test case for less-is-more effects.

Keywords: Psychology; Decision making; Heuristic; Mathematical modeling

1. Introduction

A recent approach to human judgment and rationality aims to identify simple but “ecologically rational” heuristics that require little processing power yet compare favorably to more sophisticated methods (e.g., Snook, Zito, Bennell, & Taylor, 2005). These heuristics can be construed as procedures that rely upon information latent within the structure of the environment and succeed by using this information in simple ways. In addition, the majority of such heuristics (e.g., Minimalist, Take the Best, Take the Last, the Priority Heuristic) are based on one-reason decision making (Brandstätter, Gigerenzer, & Hertwig, 2006; Gigerenzer & Goldstein, 1999; Martignon & Hoffrage, 1999, 2002). The recognition heuristic is such a procedure and is, furthermore, the first step in a number of strategies within what has been termed the adaptive toolbox (Gigerenzer, Todd, & the ABC Research Group, 1999). As such, the recognition heuristic is in many ways the cornerstone of this approach to decision making.

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The efficacy of simple heuristics has been challenged, however (e.g., Boyd, 2001; Chater, Oaksford, Nakisa, & Redington, 2003; Rossmo, 2005), and psychological investigations of the recognition heuristic in particular have produced mixed results (Andersson, Edman, & Ekman, 2005; Pachur & Biele, 2007; Pachur & Hertwig, 2006; Pohl, 2006; Snook & Cullen, 2006).

Simply stated, the recognition heuristic provides the following rule of thumb: “If one of two objects is recognized and the other is not, then infer that the recognized object has the higher value” (Goldstein & Gigerenzer, 1999, p. 41). For example, an individual may be asked to judge which of two cities has the larger population. If they recognize only one of the cities, they can use the recognition heuristic to choose the recognized city. A counterintuitive finding of great interest is the “less-is-more effect” whereby the judgments of participants who recognize only one of the cities are more accurate than those of participants who recognize both cities (Goldstein & Gigerenzer, 1999, 2002). The reason for this is the positive correlation between the likelihood of recognizing the city and the size of the city. In this task, recognition works because the probability of recognition is influenced by a mediator variable that itself reflects the “real” but inaccessible criterion. The simple recognition heuristic makes use of this information, latent in the structure of the environment, to inform judgments on the city size task—to the extent that the heuristic can outperform judgments based on city knowledge.

As a practical example, a mediating variable for magnitude-related choices, such as the cities task, might be the number of times the city has appeared in newspaper reports. This correlates with city size and influences the probability that the city name is recognized. Larger cities are more likely to be encountered (e.g., mentioned in a newspaper) and are more likely to be recognized. Smaller cities may either not have been encountered or may have been forgotten in the time since they were last encountered. Recognition, therefore, provides a cue to size. Ironically, more knowledgeable participants who recognize both cities cannot make use of this cue and must rely on other, possibly less reliable, knowledge to inform their judgments. These individuals perform poorly when, in two-alternative forced choice (2-AFC) decisions, *recognition validity* (the extent to which a correct choice can be made by recognition alone) exceeds *knowledge validity* (the probability of making the correct choice when both objects are recognized). This counterintuitive less-is-more effect has been reported in the literature (Goldstein & Gigerenzer, 1999, 2002; Reimer & Katsikopoulos, 2004; Snook & Cullen, 2006), although not all empirical studies have observed the effect (Pachur & Biele, 2007; Pohl, 2006; but see Frosch, Beaman, & McCloy, 2007).

A 2-AFC task is often used as a test-bed for magnitude judgment (or “which is best”) studies such as these because it is considered representative of the set of decisions that involve selecting a subset of objects from a larger set (Goldstein & Gigerenzer, 1999, p. 41). However, ecologically rational heuristics rely for their success on the informational structure of the environment; and when the structure of information within the environment changes (e.g., as when the information given within the choice options varies), the relative usefulness of a simple heuristic also varies (cf. Hogarth & Karelia, 2006). The appearance of counterintuitive effects, such as less-is-more, can be tracked across different task demands; and this article develops equations that describe the behavior of an idealized individual, who consistently uses the recognition heuristic. These equations are applied to a wide range of experimental situations, enabling us to identify situations where less-is-more effects are most likely to occur.

To begin with, a situation where one is required to judge, from m alternatives, which item has the greater magnitude along some dimension (e.g., which city has the highest population, which sporting team has the greatest ability) is a more generally applicable version of the 2-AFC choice task. The general model for an m -AFC situation is as follows: Let N be the population of objects from which objects on a given trial are selected; let n be the number of objects out of the total population that a participant is able to recognize; then $p(n)$, the probability of success on a given trial, is given by

$$p(n) = \sum_i \alpha_i b(i, m, n/N), \quad (1)$$

where α_i is the probability of the participant making the correct decision if exactly i out of the m objects presented on a given trial are recognized, and $b(i, m, n/N)$ is the familiar binomial probability of recognizing exactly i out of the m objects presented on a given trial, when the probability of recognizing an individual object is n/N ; i in the summation ranges from 0 to m . If the participant is to choose the greatest object, on a given trial the recognition heuristic operates as follows:

- G1: Consider the set of recognized objects.
- G2: If the set contains 1 object, select it.
- G3: If this set contains no objects, guess among the non-recognized objects.
- G4: If the set contains i objects, $1 < i \leq m$, use any available knowledge to choose between the recognized objects.

However, if, conversely, the participant is asked to choose the least object, then the recognition heuristic operates as follows:

- L1: Consider the set of recognized objects.
- L2: If the set contains $m - 1$ objects, choose the non-recognized object.
- L3: If the set contains i objects, $0 \leq i < m - 1$, guess among the non-recognized objects.
- L4: If the set contains all m objects, use any available knowledge to choose between them.

The two algorithms operate on similar principles. In both cases, choice is based on which objects are recognized, and both algorithms assume that additional knowledge is available only for recognized objects and employed only if recognition fails to produce an unambiguous choice. The two procedures differ in that, given the *greatest* question, the assumption is that the correct choice lies among the recognized objects; whereas when asked to choose the *least*, the assumption is that the answer lies among the non-recognized objects.

For the case of $m = 2$ (as studied by Goldstein & Gigerenzer, 2002), the greatest and the least tasks are equivalent. Making the binomial probabilities explicit, Equation 1 can be written as follows:

$$p(n) = \alpha_0[(N - n)(N - n - 1)]/[N(N - 1)] + \alpha_1[(2n(N - n)]/[N(N - 1)] + \alpha_2[n(n - 1)]/[N(N - 1)], \quad (2)$$

where α_0 , the probability of making the correct decision when no objects are recognized, is chance ($1/2$); α_1 , the probability of being correct when one object is recognized reflects recognition validity; and α_2 , the probability of making the correct choice when both objects are recognized, reflects knowledge validity. A less-is-more effect is predicted by Equation 2 when the plot of $p(n)$ against n forms an inverted U—that is, $p(n)$ has a maximum in the range $0 < n < N$ (see Fig. 1). This amounts to the condition that $p(n)$ is decreasing when $n = N$ —that is, that $dp/dn < 0$ when $n = N$. Differentiating Equation 2 with respect to n , and setting $n = N$, gives

$$N(N - 1) dp/dn = 2(\alpha_2 - \alpha_1)N + 1/2 - \alpha_2. \tag{3}$$

For large N , we need consider only terms of order N on the right-hand side of this equation, so we can say that dp/dn will be negative when $\alpha_1 > \alpha_2$. In other words, using Goldstein and Gigerenzer’s (2002) terminology, the potential for a less-is-more effect exists when recognition validity exceeds knowledge validity. Fig. 1, redrawn from Goldstein and Gigerenzer (2002), shows the success rate $p(n)$ derived from Equation 2 when recognition validity, α_1 , is held constant at .8 and knowledge validity, α_2 , is varied. This figure shows many curves indicating superior performance for intermediate n (number of objects recognized) than for large n —that is, a less-is-more effect.

The next question to be addressed is how this effect fares when the nature of the question is varied. As previously intimated, for 2-AFC asking which of the two objects is smaller or worse (the least question) is equivalent to asking which of the two objects is larger or best (the greatest question) because identifying which object is the greatest of two choices effectively labels the other object as the least. Thus, the information required to make the choice, and the information within the environment, are identical for both questions, and the pattern shown in Fig. 1 will also be shown in the least task. However, the distinction between *which-is-greatest* and *which-is-least* tasks becomes crucial in m -AFC problems where $m > 2$. Consider the 3-AFC task. For this task, there are four possible states of affairs: The individual might recognize three, two, one, or none of the objects. Writing out Equation 1 fully when

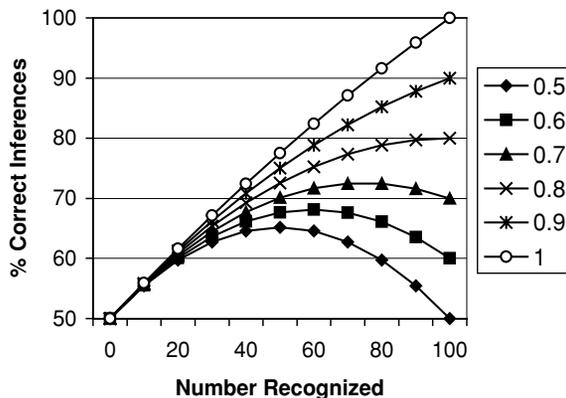


Fig. 1. The less-is-more effect for two-alternative forced choice situations. *Note:* Recognition validity is set to 0.8, and knowledge validity varies between 0.5 and 1.0 as indicated by the legend.

$m = 3$ leads to the following:

$$\begin{aligned}
 p(n) = & \alpha_0[(N - n)(N - n - 1)(N - n - 2)]/[N(N - 1)(N - 2)] \\
 & + \alpha_1[3n(N - n)(N - n - 1)]/[N(N - 1)(N - 2)] \\
 & + \alpha_2[3n(n - 1)(N - n)]/[N(N - 1)(N - 2)] \\
 & + \alpha_3[n(n - 1)(n - 2)]/[N(N - 1)(N - 2)].
 \end{aligned} \tag{4}$$

Not all the parameters can be directly associated with recognition and knowledge validity when $m > 2$, and identifying less-is-more effects is accordingly more problematic. In particular, the association of α with either recognition or knowledge validity varies according to task. In both greatest and least tasks, α_3 , the probability of making the correct choice among all recognized objects, is a measure of knowledge validity; but α_2 in the greatest task and α_1 in the least task depend partly on recognition and partly on knowledge. Our strategy is first to understand the properties of $m = 3$ performance, as characterized by Equation 4, and then consider plausible ranges of values for each of the parameters in the greatest and least tasks.

First, an obvious point: Because the less-is-more effect in Fig. 1 derives from an inverted-U relationship between performance and recognition, there will inevitably be portions of any such performance-recognition curve where the curve goes up and performance increases above chance level. The definition of a less-is-more effect as given by Goldstein and Gigerenzer (2002) is any point at which imperfect recognition of the items produces superior performance to recognizing all the items. Under these circumstances, it is trivial to demonstrate a less-is-more effect somewhere on the graph simply by assuming a level of knowledge validity (for full recognition) little better than chance. To overcome this, we focus on areas of the graph where adding to the number recognized (additional learning) reduces rather than enhances the level of performance and henceforth reserve the term *less-is-more* for these situations. A situation where recognizing more items improves performance arguably represents a trend toward “more-is-more” even if, at any given point along the curve, performance associated with incomplete recognition is superior to that obtained with full recognition. By contrast, the identification of areas where broader knowledge (higher recognition rates) actively and systematically impairs performance maps out regions where paradoxically counterproductive, and actively harmful, effects of further learning are to be found (cf. Hogarth & Karelia, 2006).

Under our definition, less-is-more effects should be associated with materials that already give rise to fairly high levels of recognition. Low levels of recognition are associated with the upward-sloping portion of the performance-recognition curve, a situation in which additional numbers of items recognized improves performance. A less-is-more effect thus defined occurs when $p(n_1) > p(n_2)$ for some n_1, n_2 , such that $0 < n_1 < n_2 < N$. This will be achieved either (a) if $p(n)$ is an inverted-U shape (as in Fig. 1 and the upper portion of Fig. 2) or (b) if $p(n)$ contains both a maximum and a minimum in the range $n = 0$ to N (the lower portion of Fig. 2). Condition (a) can be approached by differentiating $p(n)$: It is straightforward to show that when $n = N$

$$N(N - 1)(N - 2) dp/dn = 3N^2(\alpha_3 - \alpha_2) + \text{terms of order } N \text{ or less.} \tag{5}$$

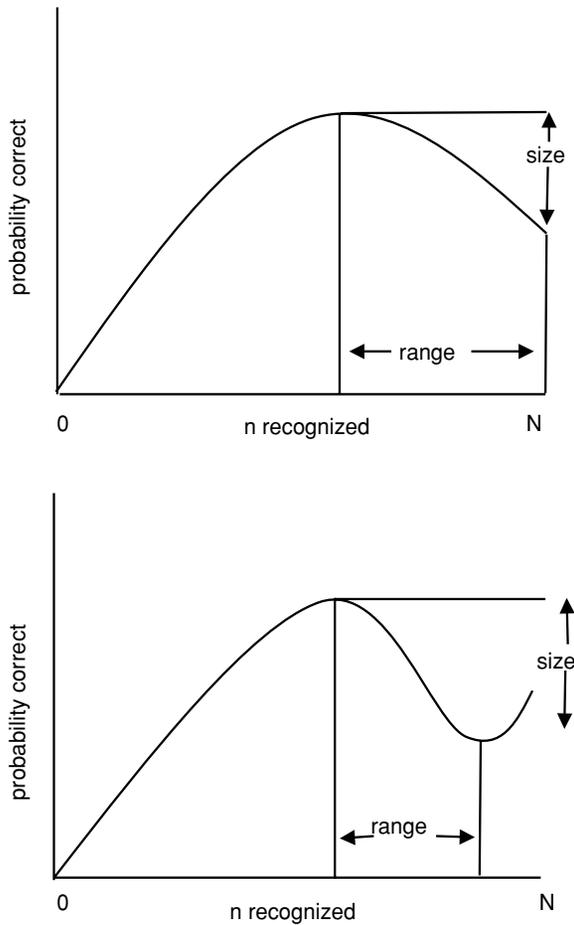


Fig. 2. Diagram demonstrating the measurement of the less-is-more effect in terms of size and range where $p(n)$ is an inverted-U function (upper panel) or an s-shaped function (lower panel).

Therefore, for large N , an inverted U will appear when $\alpha_2 > \alpha_3$. Condition (b) does not lend itself to simple analytic expressions; but $\alpha_2 < \alpha_3 < \alpha_1$, with α_1 quite large, often satisfies these conditions.

In order to delineate conditions where the use of the recognition heuristic might have real value, and additional learning be actively harmful, we set out to identify values of the parameters in Equation 4, where less-is-more effects are pronounced. The magnitude of less-is-more effects can be defined in two ways. The first is the *range* of n for which less-is-more effects prevail (i.e., the values of n for which $p(n)$, the probability of making a correct judgment, is a decreasing function of n , the total number of recognizable items). The greater the range of values that show less-is-more effects, the greater the chance of observing such effects across multiple judgments where n may vary (or across multiple participants whose n may vary). The second way of measuring the magnitude of the less-is-more effect is by comparing the peak of the probability correct function $p(n)$ with an appropriate minimum,

which will be the value of $p(n)$ when $n = N$ if $p(n)$ is an inverted-U function and the actual minimum if $p(n)$ is an s-shaped function (see Fig. 2). This difference between the peak and the appropriate minimum we call the *size* of the less-is-more effect.

Figures 3 and 4 show the range and size of less-is-more effects for the 3-AFC task, for two values of α_1 (0.8 and 0.4). Less-is-more effects are more widespread, and have larger ranges, with the larger estimate of α_1 . The calculations are based on setting N , the population of potential objects, to be 100; but similar patterns appear for any other large values of N .

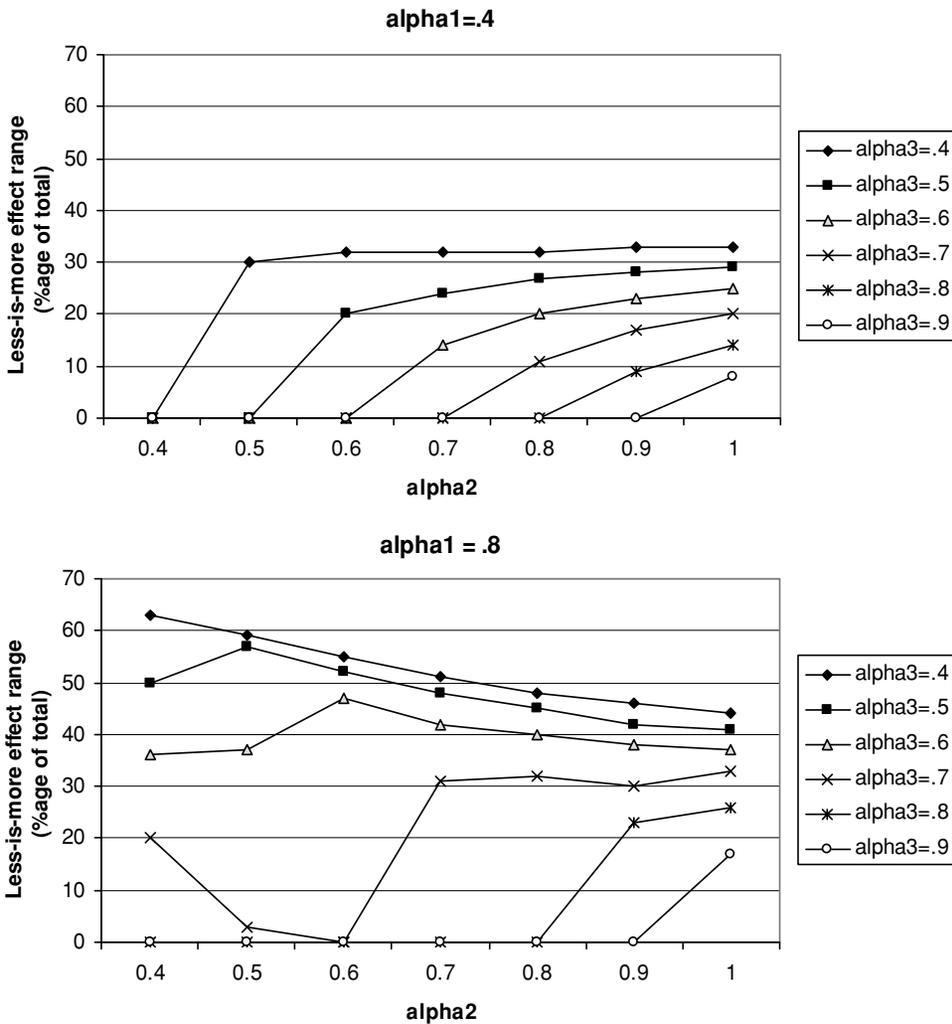


Fig. 3. Range of the less-is-more effect in the three-alternative forced choice task. *Note:* The range of values of n ($0 \leq n \leq 100$) for which df/dn is negative (a less-is-more effect) is graphed for $\alpha_1 = .4$ (appropriate for the least task) and $.8$ (appropriate for the greatest task). A range value of 0 implies $p(n)$ is monotonically increasing. A less-is-more effect with range $\geq 30\%$ might be considered large.

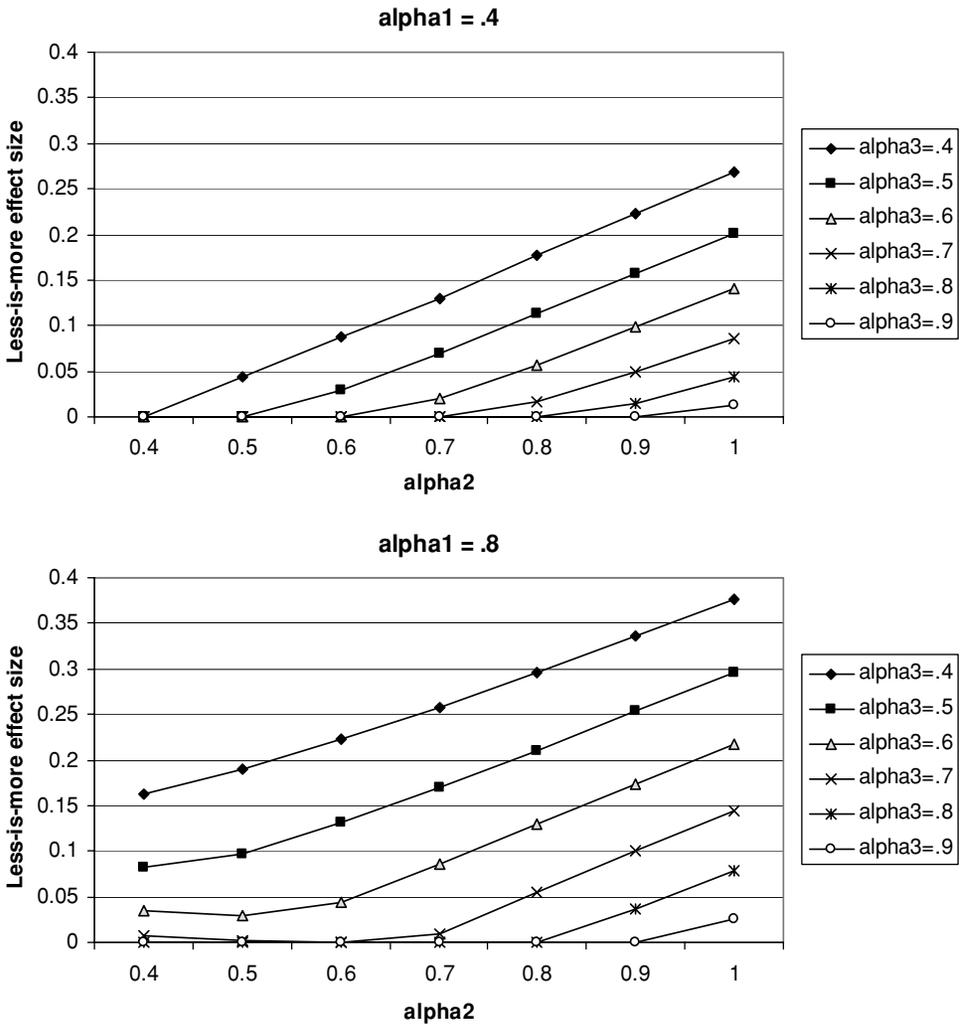


Fig. 4. Size of the less-is-more effect in the three-alternative forced choice task for $\alpha_1 = .4$ (appropriate for the least task) and $.8$ (appropriate for the greatest task). *Note:* Suppose, for $0 \leq n \leq 100$, the largest value of $p(n)$ occurs at $n = n_{max}$, then the size of the less-is-more effect is defined as the difference between $p(n_{max})$ and the smallest value of $p(n)$ for $n_{max} \leq n \leq 100$. A less-is-more effect of size ≥ 0.1 might be considered large.

We now consider how this analysis can illuminate specific tasks. When $m = 3$, the steps in the *which-is-greatest* task are outlined as (G1) through (G4) above. α_0 , chance guessing, is $1/3$. In tasks where a recognition heuristic is likely to work, it makes sense that $\alpha_1 > \alpha_2 > \alpha_3$ because the probability of making a correct decision based on recognizing only 1 item (α_1) should reflect recognition validity, and the probability of making a correct decision among 3 recognized items (α_3) reflects knowledge validity; α_2 should be larger than α_3 because it should be easier to choose between 2 recognized items than 3 recognized items. The set of parameters $\alpha_1 = 0.72$, $\alpha_2 = 0.54$, and $\alpha_3 = 0.36$ provided a reasonable fit to human performance in an experimental study of 3-AFC judgments by Frosch et al.

(2007). In their study, Frosch et al. observed superior performance for less than total name recognition on a task where participants were asked to judge either the wealthiest or the least wealthy of three celebrities. Table 1a shows that these parameters produce a less-is-more effect of moderate size and quite substantial range but, crucially, it is clear from Figs. 3 and 4 that similar conclusions can be reached with several sets of values satisfying α_1 large and $\alpha_1 > \alpha_2 > \alpha_3$.

For the *which-is-least* task, using the algorithm outlined in L1 through L4. α_0 is again chance and α_1 , the probability of success when one object is recognized, must be less than $1/2$ because the participant is guessing between two non-recognized objects. Thus, for any plausible scenario, α_1 for the least task $<$ α_1 for the greatest task; α_2 , the probability of success when two objects are recognized, should be quite large if recognition validity is high because the algorithm requires selection of the non-recognized object. Frosch et al. (2007) estimated $\alpha_1 = 0.36$, $\alpha_2 = 0.72$, and $\alpha_3 = 0.36$. Table 1a shows that with these parameters a less-is-more-effect size of 0.162 and range of 30% are predicted. The size is comparable to that in the *which-is-greatest* task (0.205), but with the range much diminished (from 54%). This suggests that the less-is-more effect is less widespread and more difficult to detect in *which-is-least* judgments. Fig. 5 shows performance in the two tasks using the parameters suggested by Frosch et al. Again, Figs. 3 and 4 show the same conclusion holds for other parameter choices.

To summarize the mathematics for “which is greatest” questions, recognition is helpful when few objects are recognized. For “which is least” questions, (lack of) recognition is only helpful if many objects are recognized. “Greatest” questions will, therefore, have larger

Table 1
Parameter values and magnitude of the less-is-more effect in the *m*-alternative forced choice task

(a) <i>m</i> = 3 Plausible Values				Less-is-More Effect				
Task	α_1	α_2	α_3	Size	Range			
Greatest	0.72	0.54	0.36	0.205	54%			
Least	0.36	0.72	0.36	0.162	30%			
(b) Extreme Values				Less-is-More Effect				
<i>m</i>	Task	α_1	α_2	α_3	α_4	α_5	Size	Range
2	Greatest	1	0.5				0.253	50
	Least	0.5	1				0.253	50
3	Greatest	1	0.5	0.33			0.341	62
	Least	0.5	1	0.33			0.341	38
4	Greatest	1	0.5	0.33	0.25		0.388	70
	Least	0.33	0.5	1	0.25		0.388	30
5	Greatest	1	0.5	0.33	0.25	0.2	0.416	75
	Least	0.25	0.33	0.5	1	0.2	0.416	25

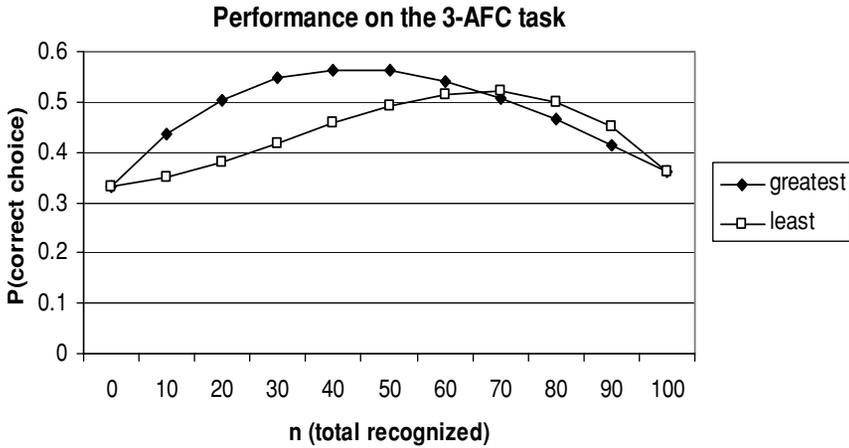


Fig. 5. Graph of three-alternative forced choice (3-AFC) probability correct for plausible parameters of the least and greatest tasks.

ranges because the peak always comes earlier (i.e., at lower recognition rates) than for “least” questions. This means that further learning (higher recognition rates) is actively harmful for more of the time. There is no asymmetry of size of effect when alphas take complementary values for the two questions, as in Frosch et al. (2007).¹ These results are not restricted to 3-AFC but can be extended to larger values of m (the number of objects the participant must choose between). For tractability, attention is confined to extreme cases where the recognition heuristic works perfectly. This is unrealistic, but the general shapes of the $p(n)$ should be similar in situations where use of the recognition heuristic is plausible (high recognition validity, little knowledge). For the which-is-greatest task, $\alpha_0 = 1/m$ and $\alpha_i = 1/i$, $0 < i \leq m$. For the which-is-least task, $\alpha_i = 1/(m-i)$, $0 \leq i < m$ and $\alpha_m = 1/m$. These results follow directly from the participant needing to guess among either i recognized or $m-i$ non-recognized objects. Table 1b shows the size and range of the less-is-more effect for these extreme cases, for m from 2 through 5. The curves become more skewed as m increases, with the positively skewed curves for the greatest task showing a greater range for the less-is-more effect than the negatively skewed curves for the least task. Fig. 6 shows this for $m = 3$ and 4.

In sum, greater ranges of the less-is-more effect will occur with the which-is-greatest than the which-is-least task, rendering recognition more effective relative to knowledge on this task because recognition is more helpful for lower recognition rates. This is not obvious on the basis of 2-AFC studies alone. The range of the less-is-more effect for the which-is-greatest task also increases the greater the value of m (the number of objects the participant has to choose between), indicating that the relative utility of incomplete knowledge increases alongside the number of choices available. This again follows from the observation that recognizing few of the available choices produces a level of success that further learning erodes. This result formally expands the applicability of recognition-based inference but implies that the classic 2-AFC task developed by Goldstein and Gigerenzer (2002) may not be the most sensitive paradigm for studying less-is-more effects (and, by extension, the recognition heuristic).

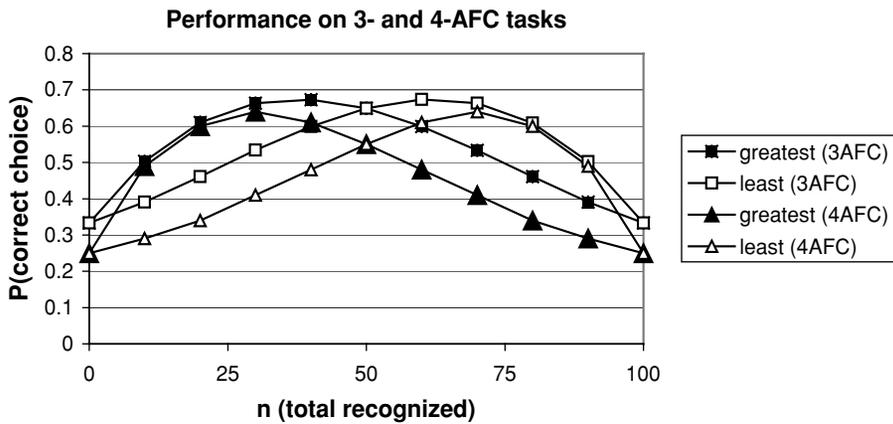


Fig. 6. Graph of three-alternative forced choice (3-AFC) and four-alternative forced choice (4-AFC) probability correct for the lesser and greater tasks with extreme parameters (perfect recognition validity, zero knowledge validity).

Note

- Where complementary refers to the following equalities between greatest and least: α_0 greatest = α_0 least, α_1 greatest = α_2 least, α_1 least = $.5 \times \alpha_2$ least, α_3 greatest = α_3 least. Thanks to David Danks for this elegant formulation.

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