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Article

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COMMENT

A little more learning:

A re-analysis of ignorance-driven inference in Frosch, Beaman & McCloy (2007)

C. Philip Beaman

School of Psychology & Clinical Language Sciences, University of Reading

Earley Gate,

Whiteknights,

Reading RG6 6AL, UK

Email: c.p.beaman@reading.ac.uk

Tel: +44 (0) 118 3787637

Fax: +44 (0) 118 3786715

Running Head: UPDATE ON IGNORANCE-DRIVEN INFERENCE

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In their study on ignorance-driven inference, Frosch, Beaman and McCloy (2007) reported a "less-is-more effect" (LiME) such that, when asked to judge the relative wealth of individuals, judgments were reliably more accurate when individuals did not recognise all of the names presented than when all the names were known. For example, participants might be more accurate when asked to compare the relative wealth of Mick Jagger and A.N. Unknown than when asked to compare the relative wealth of Mick Jagger and Keith Richards.

This outcome arose from the prediction that participants apply a *recognition heuristic* (RH; Goldstein & Gigerenzer, 2002) that is, they use fame as a surrogate for wealth without accessing any further information about the recognised individual. A LiME occurs if wealth and fame are positively correlated and recognition is a more accurate predictor of wealth (when contrasting a known with an unknown individual) than knowledge (when contrasting two known individuals). The RH is applicable across a variety of relative judgments (e.g., the size of cities, the profitability of shares, the infectiousness of diseases, the success of sports teams) and is the first step in a class of simple heuristic decision-making strategies in which the minimum information necessary to provide a basis for judgment is searched or employed (Gigerenzer, Hertwig & Pachur, 2011).

Frosch et al. (2007) concluded, in support of the RH, that "participants reliably use recognition as a basis for their judgments" (p. 1329) but, as an existence-proof, Beaman, Smith, Frosch and McCloy (2010) demonstrated how LiMEs might arise as a consequence of limited access to information about known items or individuals rather than choosing not to search for such information. Beaman et al. (2010) argued that many models with these properties would show similar behaviour but were unable to present empirical data to support this conjecture. Relevant, but previously overlooked, data are however available in Frosch et al. (2007). Figure 1 shows the data from Frosch et al. (2007) for a comparison when participants were asked "which of these two individuals is the richest?" presented in terms of the frequency of all choices rather than the percentage correct choices, and also breaks down the data into whether the choice was in accordance with the RH. Viewing the data in this way reveals that the advantage for only recognising one of the individuals from the pair is apparent not only when participants' choices are consistent with the RH but also when they seemingly disregard the RH and judge that the unrecognised individual is the wealthier of the two. Although this occurs only rarely (41 compared to 167 when the recognised individual was chosen) it is not predicted by the RH. This result was not obvious from the original analysis, which focussed on judgments in favour of the recognised option and the relative accuracy of judgments made when only one option was recognised. However a success rate which included these data-points where one option was recognised but the non-recognised option was chosen cannot ascribe all of this "ignorance-driven inference" advantage to RH usage. This is the first point to arise from this re-analysis.

FIGURE ONE ABOUT HERE

To determine the extent to which the RH is used, Hilbig, Erdfelder and Pohl (2010) introduced a measurement model, using multinomial processing tree techniques. The model consists of three decision trees which describe the possible decisions made given the recognition situations (recognise 0, 1 or 2 options) presented in Figure 1. The model is shown in Figure 2.

FIGURE TWO ABOUT HERE

Each branch of the tree is associated with a parameter which estimates the probability that branch is followed. The product of the parameters on a particular path gives the expected number of outcomes of that kind. So, if one option is recognised, the probability of using the RH is *r*, the probability that the correct response is given is *a.* The probability that the RH is used successfully is therefore *r a.* Parameters are estimated given known constraints such as the total number of times exactly one item is recognised is known and the total number of times the correct response is given. The fact that a recognised option is chosen does not rule out the possibility that the RH is discarded and knowledge other than simple recognition is employed: Participants of a cautious nature might search for confirmatory evidence that Mick Jagger is sufficiently wealthy to choose over the unknown Fred Bloggs. A famous name for whom the information is available that s/he recently filed for bankruptcy might result in a deliberate choice against the RH. Applying Hilbig et al's model using multiTree software (Moshagen, 2010) the best-fitting set of parameters indicate that *r*, the estimated probability that the RH is employed is .57[1] The expected results of this model are shown in Figure 3 and these do not differ significantly from the observed data, G^2 = 1.15, *df* = 1, *p* = .28.

FIGURE THREE ABOUT HERE

These results do not invalidate Frosch et al's (2007) observation of a less is more effect, but they indicate that the reasons behind this effect may differ from those assumed. Previously, it was concluded that the RH was employed approximately 80% of the time in the situation considered here and the less-is-more effect was taken both as a consequence of participants using this heuristic and as further evidence for the widespread application of the heuristic. However, if the model is rerun with *r*=.80 then the results differ significantly from the data, G^2 = 22.49, *df* = 2, *p* = .00001. The current analysis suggests instead, the heuristic was employed only a little over half the time and the less-is-more effect therefore cannot be ascribed wholly to the use of the heuristic (indeed, Figure 1

[1] Other estimated parameter values are *a* (recognition validity) = .78, *b* (knowledge validity) = .58 and *g* (guessing validity) = .52. The fit is improved if g is not allowed to vary and set at a constant .5 (G^2 = .1.43, *df* = 2, *p* = .49 but the other parameter values do not change and this version of the model is not significantly different from the original (G^2 = .28, *df* = 1, *p* = .60)

implies a LiME for other strategies) and its appearance in any future data-set should not therefore be taken as unequivocal evidence that such a heuristic was universally employed.

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FIGURE LEGENDS

Figure 1.: Data redrawn from the two-alternative forced choice task of Frosch et al. (2007) when participants are asked “Which of these two individuals is the wealthiest?” The frequency of different choices is broken down by the number of options recognised (out of a maximum of two), whether the choice was consistent with the recognition heuristic (RH) when applicable, and whether the choice was correct.

Figure 2: Graphical depiction of Hilbig et al.’s (2010) measurement model. The top decision tree represents the situation when neither of the options are recognised and *g* is the probability of a correct choice. The middle decision-tree represents the situation when only one option is recognised. In this situation, *r* is the probability of using the recognition heuristic (RH), *a* is the probability that the recognition heuristic gives the correct answer and b is the probability of a correct choice based upon knowledge. The bottom decision tree represents the situation when both options are recognised and *b* is once again the probability of a correct choice based upon knowledge.

Figure 3.: The expected results for the best-fitting model applied to the data presented in Figure 1 when all parameters are allowed to vary. The expected frequency of different choices is broken down by the number of options recognised (out of a maximum of two), whether the choice was consistent with the recognition heuristic (RH) when applicable, and whether the choice was correct.

FIGURE ONE

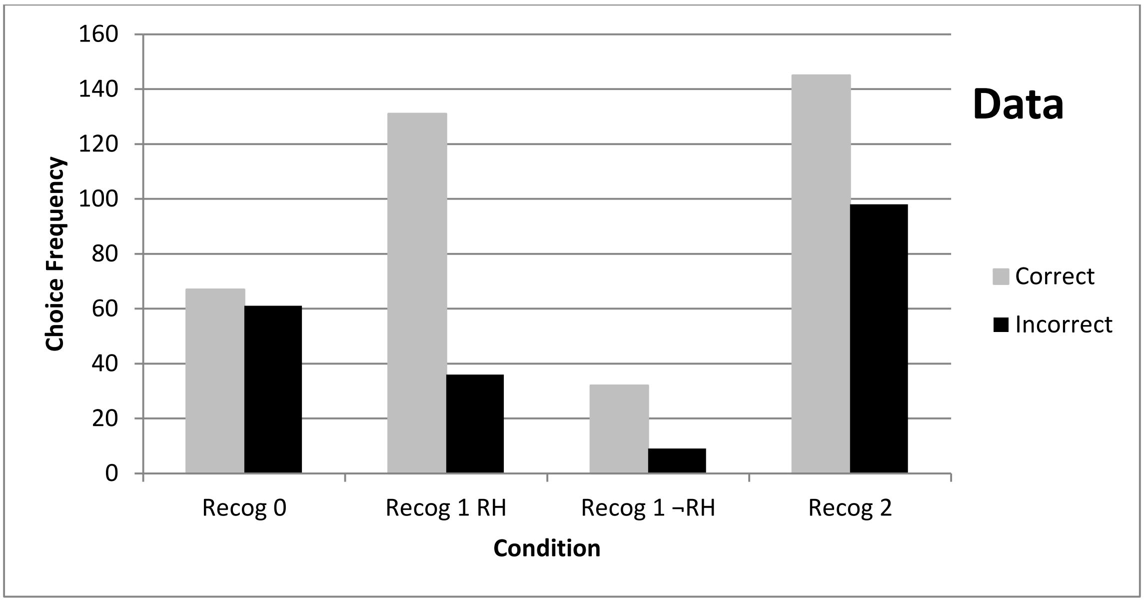
Data
Choice Frequency
160
140
120
100
80
60
40
20
0
Recog 0
Recog 1 RH
Recog 1 ¬RH
Recog 2
Condition
Correct
Incorrect

FIGURE TWO

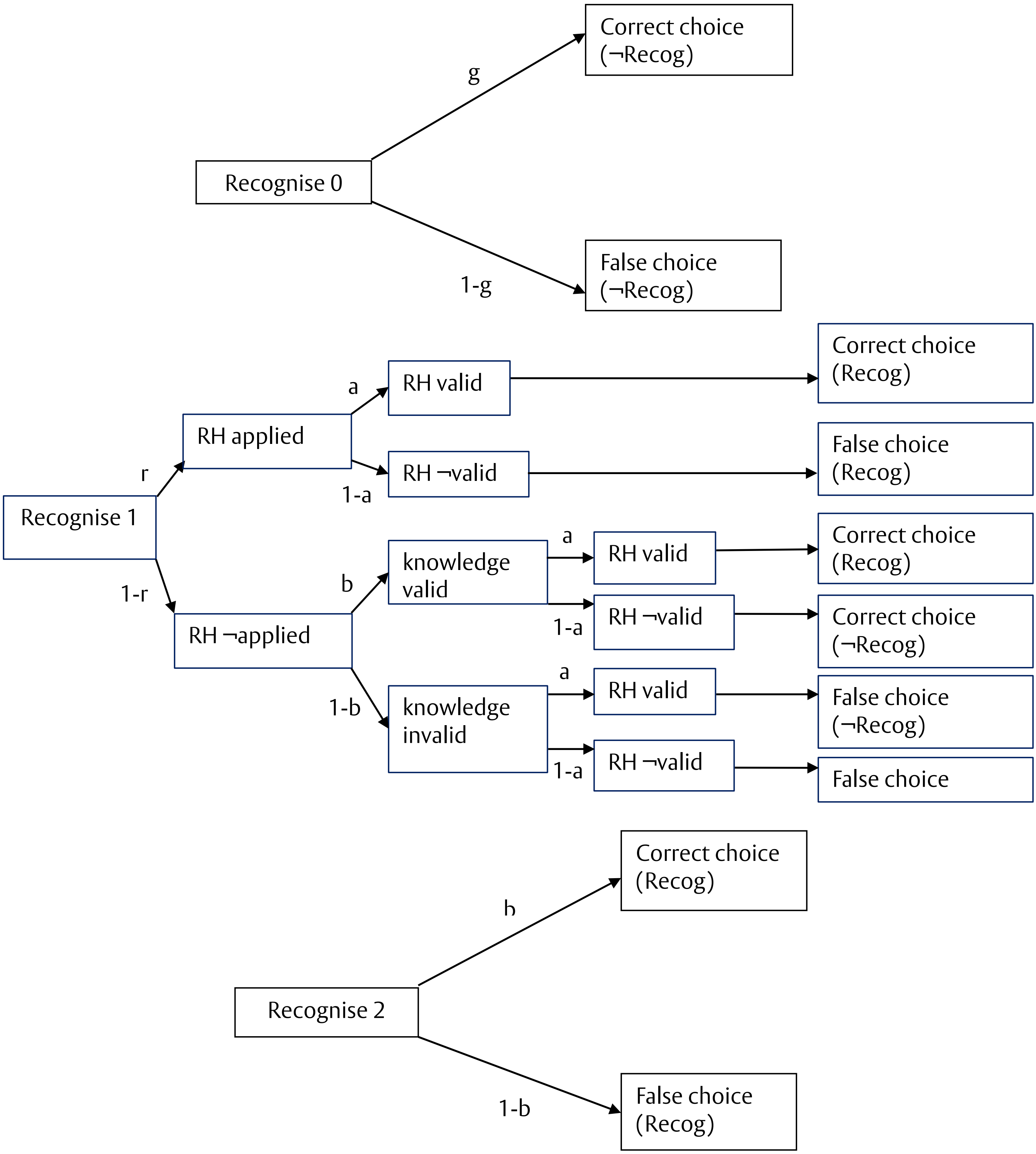
Recognise 0
g
Correct choice (¬Recog)
1-g
False choice (¬Recog)
Recognise 1
r
RH applied
a
RH valid
Correct choice (Recog)
1-a
RH ¬valid
False choice (Recog)
1-r
RH ¬applied
b
knowledge valid
a
RH valid
Correct choice (Recog)
1-a
RH ¬valid
Correct choice (¬Recog)
1-b
knowledge invalid
a
RH valid
False choice (¬Recog)
1-a
RH ¬valid
False choice
Recognise 2
b
Correct choice (Recog)
1-b
False choice (Recog)

FIGURE THREE