The Rationality of Different Kinds of Intuitive Decision Processes

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Abstract

Whereas classic work in judgment and decision making has focused on the deviation of intuition from rationality, more recent research has focused on the performance of intuition in real-world environments. Borrowing from both approaches, we investigate to which extent competing models of intuitive probabilistic decision making overlap with choices according to the axioms of probability theory and how accurate those models can be expected to perform in real-world environments. Specifically, we assessed to which extent heuristics, models implementing weighted additive information integration (WADD), and the parallel constraint satisfaction (PCS) network model approximate the Bayesian solution and how often they lead to correct decisions in a probabilistic decision task. PCS and WADD outperform simple heuristics on both criteria with an approximation of 88.8% and a performance of 73.7%. Results are discussed in the light of selection of intuitive processes by reinforcement learning.

1. Introduction

Classic work in judgment and decision making indicates that intuitive processes can lead to systematic deviations from rationality often referred to as biases (for an overview, see Gilovich, Griffin, & Kahneman, 2002). Biases were thereby used to diagnose the use of certain judgment heuristics which were assumed to be (partially) based on intuitive processing. The representativeness heuristic posits, for example, that persons' probability judgments are influenced by the degree to which a target is seen as representative for a category. Observations of a conjunction fallacy—as demonstrated in the classic Linda-is-a-bank-teller vignette—were explained by the representativeness heuristic (e.g., Kahneman & Frederick, 2002).

This seminal work was crucial to highlight the role of intuition which has often been neglected in mainstream decision research. The approach, however, also had several limitations. First, the exact processes that produce feelings of representativeness were not specified, and therefore predictions remained imprecise. Second, intuition research in judgment and decision making was not sufficiently connected to work in cognitive psychology that aims to specify processes underlying intuition. Third, since tasks were constructed such that the use of intuitive heuristics leads to deviations from rationality, intuition was per operationalization doomed to lead to wrong decisions, which has hindered the detection of intuition's merits (Lopes, 1991).

Recent intuition research has aimed to overcome all three limitations. Hogarth (2001), for example, suggested a model that describes the cognitive processes underlying intuition and opened the view towards situations in which intuition might be successful (Hogarth, 2005). According to his model, the quality of intuitive decisions crucially depends on the learning environment. Other researchers went one step further and developed precise computational models for intuitive processes in judgment and decision making based on general models of memory (Dougherty, Gettys, & Ogden, 1999), perception (Betsch & Glöckner, 2010; Busemeyer & Townsend, 1993; Glöckner & Betsch, 2008a; Holyoak & Simon, 1999; Thagard & Millgram, 1995; Usher & McClelland, 2001), or the idea of automatic serial production rules (Gigerenzer, Todd, & The ABC Research Group, 1999).

Reviewing this multitude of cognitive processes, Glöckner and Witteman (2010) argue that the concept of intuition is often used too broadly as an umbrella term for many kinds of different processes. There are most likely several qualitatively different kinds of cognitive processes that produce feelings of how to decide without knowing why (Claxton, 1998) and that unconsciously influence our choices

(Bargh & Chartrand, 1999).

In the current paper, we report results from a simulation that investigates how (some of) the suggested mechanisms underlying intuition perform in probabilistic inferences. Specifically, we generate all possible decision tasks for choices between two alternatives based on six probabilistic binary cues. The rational solution for this kind of task, i.e., the integration of cues coherent with the axioms of probability theory, can be calculated according to Bayes' theorem.[1] We were interested in three related questions: a) how often do the mechanisms lead to choices that are in line with the rational choice (*mimicry*), b) how often would mechanisms lead to correct choices (*performance*), and c) which factors of the environment influence performance of each mechanism (*moderators*).

2. Previous Work

One reasonable assumption is that more complex and effortful decision strategies generally lead to better decisions (Beach & Mitchell, 1978). Some studies, however, show that this assumption does not hold in all environments. Payne et al. (1988), for example, show that under time constraints simple lexicographic strategies (LEX; i.e., compare options by most probable outcomes and decide in favor of one option if one outcome differentiates between options) can lead to better decisions than weighted linear models such as weighted additive (WADD; i.e., weight outcomes by probabilities and add them up). Also, simple heuristics like LEX were shown to perform well with respect to accuracy in several real-world settings in which an outside criterion for assessment was available (Czerlinski, Gigerenzer, & Goldstein, 1999; Gigerenzer & Brighton, 2009; but see also Hilbig & Richter, 2011). More systematic investigations of the performance of LEX and other decision rules in probabilistic inferences show that strategy performance depends on the match between decision rule and environment (Hogarth & Karelaia, 2007). Hence, certain strategies may be tailored to be successful in specific environments.

3. Aims of the Current Study

In the current study we extend this previous work. First, we extend the scope of modeling by including a network model (PCS) in addition to the standard mechanisms TTB, WADD, and EQW. TTB is a prominent representative of LEX algorithms and EQW is a simple heuristic that sums up unweighted

[1] See, however, Cohen (1981) for a discussion on the rationality of Bayesian inference.

cue values. Automatic implementations of TTB and EQW are processes underlying intuition according to Gigerenzer (2007). Furthermore, various decision models in the literature predict choices that follow weighted linear information integration (Busemeyer & Townsend, 1993; Roe, Busemeyer, & Townsend, 2001). To avoid complex model simulations for those models, we used two implementations of WADD to approximate their performance. Furthermore, we added variants of PCS (i.e., PCS_1, PCS_2) which has been shown to account well for decisions (Glöckner & Betsch, 2008b), confidence, and response time (Glöckner & Betsch, 2012; Glöckner & Bröder, 2011), coherence effects (Glöckner, Betsch, & Schindler, 2010; Holyoak & Simon, 1999), and arousal (Hochman, Ayal, & Glöckner, 2010) in probabilistic inferences. According to PCS, the mental representation of a task is modeled as a connectionist network including salient cues and options as interconnected nodes and their subjective validities and cue patterns as connection weights (see Figure 1). Initial advantages of one option are accentuated by a spreading activation mechanism that highlights cues favoring this option and devaluates cues speaking against it. PCS thus mimics coherence processes in which the interpretation of a decision situation is simplified by a systematic re-evaluation of information. The two variants of the PCS model used in the simulations differ in the k parameter of the transformation function (see Figure 1, lower right). Parameter k can be interpreted as the individual sensitivity to differences between validities. For $k = 0$ ($k \to \infty$) the relative weight between differing validities is 1 ($\to \infty$), that is, an individual shows no (infinite) sensitivity towards differences in validities. In past studies, individually fitted k parameters varied between 1 and 3. For $k = 1$ (i.e., PCS_1), transformation is linear, whereas for $k = 2$ (i.e., PCS_2), transformation is quadratic and thus reflects accentuation of cues due to higher sensitivity (Glöckner & Bröder, 2011, p. 27).

Second, we do not use a few sampled environmental constellations only. To estimate the total performance, we include all distinct tasks of choices between two options based on six probabilistic cues by combining all possible cue patterns with all validity patterns. We classify these tasks along different dimensions to learn about which environmental conditions render which kind of intuition most successful.

Third, we determine the extent to which models mimic rational choice, and additionally we determine the performance of the models as the relative number of (expected) correct choices in the environment. We therefore assess the degree to which intuitive mechanisms "violate coherence with the implications of statistical theory" (Hogarth & Karelaia, 2007, p. 734), as formulated in the coherence criterion of rationality, whereas earlier work often relied on the correspondence criterion of rationality, that is, the extent to which models correspond with an outside criterion.

4. Simulation

We assessed mimicry of the rational model and performance for different processes that are assumed to underlie intuition in probabilistic inferences.

4.1 Environments

We investigated probabilistic decision making between two options with six binary cues. We included all distinct tasks fully crossed with all possible sets of cue validities. From the total set of tasks resulting from all cue patterns (i.e., 2×6 cues with binary outcomes: $2^6 \times 2^6 =$ 4,096), we generated a reduced set by excluding conceptually identical tasks. We dropped patterns that a) were option-reversed, b) differed in the sign of non-discriminating cues only (i.e., $--$ vs. $++$), and c) did not differentiate between options at all which resulted in a qualified set of 364 cue patterns. In a second step, we generated a reduced set of cue validity combinations for the six cues using interval sampling. That is, we generated all combinations of cue validities ranging from .51 to .99 in steps of .03 for six cues and ordered each combination from the highest to the lowest cue validity. Note that the order of validities is negligible as long as all qualified tasks of an environment are sampled. We then deleted all multiples with identical cue validities and combinations that contained the same cue validity at least twice to assure that TTB makes unambiguous predictions. This resulted in 12,376 combinations of validities in total.

4.2 Models for Intuitive Processes

The simulation involved two simple heuristics, TTB (take-the-best) and EQW (equal weight) from the adaptive toolbox (Gigerenzer, Todd, & The ABC Research Group, 1999); two implementations of weighted additive models (WADD) representing a whole class of intuition models, and neural network implementations of intuitive processes according to Parallel Constraint Satisfaction (PCS; Glöckner & Betsch, 2008a) differing in the sensitivity parameter k (see above). For each model and the rational solution, the choice rule is described in Table 1.

4.3 Dependent Variables

For each task, we determined the rational choice according to naïve Bayes and compared it against the choices that result from applying the respective intuition model. We determined the posterior probability (i.e., p_n^{Bayes}) of the more probable of two options in task n given the cues by assuming equal priors for each option and independence of cues (compare with Lee & Cummins, 2004, Formula 1, p. 345):

$$p_n^{Bayes} = \begin{cases} \frac{p(A>B|cues)}{p(A>B|cues)+p(B>A|cues)} = \frac{\prod_{i\in\text{FA}} v_i \times \prod_{i\in\text{FB}}(1-v_i)}{\prod_{i\in\text{FA}} v_i \times \prod_{i\in\text{FB}}(1-v_i)+\prod_{i\in\text{FB}} v_i \times \prod_{i\in\text{FA}}(1-v_i)} & \text{if } \geq .50 \\ 1-\frac{p(A>B|cues)}{p(A>B|cues)+p(B>A|cues)} & \text{if } < .50 \end{cases} \quad (1)$$

The numerator is the product of validities over all cues favoring option A (i.e., FA) times the product of (1 - validities) over all cues favoring option B (i.e., FB), which constitutes the probability of A being greater than B for the observed cues. The denominator constitutes the sum of the nominator and the probability of B being greater than A given the cues. Put differently, the probability of the target event given the cues is set in proportion to the sum of the probabilities of all possible events given the cues.

Our first dependent measure *mimicry* of the rational solution is measured as the percentage of choice overlap between the Bayesian and each intuition model. Note that the rational solution could either suggest one or be inconclusive between options. Thus, a baseline of 33.3% of choice overlap can be expected by chance. The second dependent measure is performance, which is the percentage of correct choices that can be expected when applying model k (i.e., p^k). Hence, expected performance of each model over all tasks $n = 1 \ldots N$ can be calculated by:

$$p^k = \sum_{n=1}^{N} \frac{1}{N} \times \begin{cases} p_n^{Bayes} & \text{if model } k \text{ overlaps with } Bayes \\ 1 - p_n^{Bayes} & \text{if model } k \text{ does not overlap with } Bayes \\ .50 & \text{if model } k \text{ is inconclusive} \end{cases} \quad (2)$$

If the model (does not) overlap(s) with the Bayesian solution, the probability for a correct decision equals the (complementary) probability according to Bayes. If the model does not make a prediction, a choice is based on guessing and thus correct with a probability of .50 (assuming that options always differ on the criterion).

Hence, mimicry measures the approximation of the Bayesian solution, whereas performance measures the expected accuracy of resulting choices.

4.4 Design

We determined mimicry and performance based on a complete crossing of the reduced sets of tasks and validities (i.e., $364 \times 12,376 = 4,504,864$ choices). To investigate potential moderators, the influence of three variables capturing characteristics of the task on these measures was analyzed. We categorized tasks as easy, intermediate or hard according to the posterior probability of the more probable option p_n^{Bayes}. A task n is categorized as hard if $p_n^{Bayes} < .65$, as easy if $p_n^{Bayes} > .85$, and as intermediate for values in-between.[2] We further categorized tasks according to the mean and the standard deviation (SD) of the set of six cue validities. That is, a task is categorized as a low mean (SD) task if the mean (SD) of its validities belongs to the bottom 25% of all means (SDs), as high if it belongs to the top 25% of all means (SDs), and as intermediate for values in-between.[3] In total, the simulation consisted of 6 (models) $\times$ 3 (task difficulty) $\times$ 3 (mean of validities) $\times$ 3 (standard deviation of validities) $=$ 162 conditions.

4.5 Hypotheses

We predict less mimicry of the rational choice model and lower performance with increasing task difficulty (H1). If a task is easy, that is, if cues strongly support one option, it is (more) likely that all models are in line with the rational choice. We further predict less mimicry with increasing mean validities (H2). This hypothesis rests on the observation that for extreme probabilities (e.g., cue validities) linear approximations of rational solutions tend to become worse (Juslin, Nilsson, & Winman, 2009). Finally, based on previous work (Hogarth & Karelaia, 2007), we predict that the performance and mimicry of models depend on the standard deviation of cue validities. With increasing standard deviation the environment becomes less compensatory. Non-compensatory information integration algorithms such as TTB should be better in mimicry of the rational choice model in non-compensatory (as compared to compensatory) environments (and vice versa for EQW) (H3). An algorithm that successfully approximates the rational solution will be chosen more frequently by adaptively learning

[2] Specific cutoff values are arbitrary. We provide a regression analysis in the next section that supports our conclusion from the plotted data.

[3] We checked that the pattern of results is not dependent on the exact values chosen as categorization criteria.

individuals over time. Due to the observed prevalence of PCS in probabilistic inferences in past studies, we therefore predicted that PCS would provide the best approximation in the model comparison (H4).

5. Results

5.1 Mimicry of Rational Solution

In line with our hypothesis, PCS_2 shows the highest overlap (88.8%) with the rational choice model averaged over all tasks (Figure 2, left panel). The other models–except for EQW–also overlap considerably well with the rational solution ($WADD_{corr}$ = 86.5%, TTB = 83.3%; EQW = 57.6%). Averaged over all environments and strategies, the percentage of overlap increases from 63.3% to 94.7% with decreasing task difficulty (Figure 2, middle left panel), supporting our first hypothesis. Furthermore, we observe that overlap decreases from 83.8% to 74.0% when the mean of cue validities increases (middle right panel), which supports our second hypothesis. Without being hypothesized, we also observe that overlap decreases from 82.1% to 76.2% when the standard deviation of cue validities increases (right panel).

To explore interactions between models and task characteristics, all conditions are plotted in Figure 3. All models are affected similarly by task difficulty and the mean of cue validities. Choice overlap is lower for difficult tasks and tasks with a high mean of cue validities. In accordance with H3, model overlap depends on the standard deviation of cue validities. The mimicry of rationality of the compensatory models decreases with increasing standard deviation (model average: from 82.4% to 74.3%). Overlap, however, increases with increasing standard deviation of cue validities for the non-compensatory model from 80.5% to 86.0%.

5.2 Performance

As a second dependent variable we analyzed the performance of each model, that is, the expected proportion of correct choices in the environment (i.e., p^k, see Formula 2). Averaged over all conditions, PCS_2 shows the highest performance with 73.7% correct choices, closely followed by $WADD_{corr}$ with 73.1%, TTB with 71.8%, PCS_1 with 70.1%, $WADD_{uncorr}$ with 69.2%, and EQW with 64.9%. For difficult tasks, all models are close to chance level of .50 (Figure 4, left panel). For easy tasks (right panel), PCS_2, $WADD_{corr}$, and TTB are close to 100%. For tasks with intermediate difficulty (middle panel), PCS_2 and $WADD_{corr}$ lead on average to higher performance (71.1% and 70.3%) than TTB (68.4%).

Note that there exist few constellations in which TTB outperforms all other strategies. This is the case if the mean of the cue validities is low to intermediate and the standard deviation of validities is high (i.e., when the environment is non-compensatory).

5.3 Predicting Mimicry of Rational Solution

To predict the overlap with the rational solution for different environments, we conducted a logistic regression predicting mimicry of the Bayesian choice by environmental factors and type of model (Table 2). In line with the results already reported, overlap increases for easier tasks, but decreases with increasing average and standard deviation of cue validities. The coefficients represent changes in odds (i.e., p/(1-p)) that result from one unit change in the predictor. Odds above 1 indicate positive predictors. The odds for an overlap with the rational choice model, for example, are twice as high for PCS_2 in comparison to TTB when controlled for task difficulty, mean validities, and the standard deviation of validities in a logistic regression. Conversely, the odds reduce by factor 0.003 (= 1 / 333.3) when cue mean validities (hypothetically) change by 1 point.

We also tested an extended regression model in which all two-way interaction terms of strategies with standard deviation of validities were included. In line with our interaction hypothesis (H3), with increasing standard deviation of validities the odds for an overlap with the rational choice model decrease for all compensatory models in comparison to TTB, although the effect of the additional interactions is negligible (Δ Pseudo $R^2 = .01$) and therefore results are not displayed here.

6. Discussion

In many everyday decisions persons will not have the time and/or the cognitive capacity to calculate rational solutions deliberately. Persons have to rely on approximations of rationality based on simplified deliberate rules and/or on automatic-intuitive processes. In the current paper we have investigated the degree to which different algorithms suggested to describe intuitive processes approximate the rational solution.

In line with our expectation, we observed that overall a parallel constraint satisfaction model showed highest mimicry of the rational solution (88.8%) and thus also best performance (73.7%)

among all considered models. Assuming that individuals learn to select particularly successful algorithms over time (from an ontogenetic and phylogenetic learning perspective), this converges with previous findings indicating that PCS processes seem to prevail in probabilistic inferences (see introduction for references).

However, a chance corrected weighted additive algorithm which was used as placeholder for other complex models of intuition (e.g., Busemeyer & Townsend, 1993) fared only slightly worse concerning performance than PCS. Simple heuristics showed lower performance on average, although there were a few environmental constellations (high SDs of validities) in which TTB outperformed all other models. Furthermore, it should be kept in mind that our results on model performance are based on the simplifying assumption that all distinct choice problems have an equal probability of appearing in the real world, which might be debatable. Nevertheless, overall mimicry and performance seem to be generally robust since PCS also performs best for the majority of considered problem subsets.

We were also able to identify environmental moderators of mimicry and performance. As expected, mimicry and performance is higher for easier tasks and for tasks with low average cue validities. We also showed that compensatory models have better mimicry for compensatory environments (i.e., low standard deviation of cue validities), as compared to more non-compensatory environments (i.e., high standard deviation of cue validities), and vice versa for non-compensatory mechanisms. Considering the overall dominance of PCS and $\text{WADD}_{\text{corr}}$, it might be questioned from a reinforcement learning perspective whether the advantage in performance of TTB under few environmental conditions would be sufficient to make persons choose this algorithm.

Overall, we conclude that implementations of intuitive processes that rely on PCS or chance-corrected weighted additive cue integration approximate the rational solution very well. Considering that Bayesian calculations are effortful and connected with high opportunity costs, and taking into account that even small errors in these deliberate calculations can lead to severe mistakes (Hammond, Hamm, Grassia, & Pearson, 1987), it will often be optimal–even based on rational strategy selection considerations (Beach & Mitchell, 1978)–to apply quick automatic-intuitive information integration algorithms such as PCS instead of slow deliberate Bayesian calculation.

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TABLES

Table 1: Models and choice rules.

Class of Models	Name of Model	Choice Rule
rational choice	naïve Bayes	choose the option with the higher probability assuming–for matters of simplification–equal priors for both options and independence of cues
adaptive toolbox	take-the-best (TTB)	choose the option according to the most valid cue that discriminates between options
	equal weighting (EQW)	choose the option with the higher number of positive cue values
weighted additive	weighted additive uncorrected ($WADD_{uncorr}$)	choose the option with the higher sum of cue values weighted by cue validities that are not corrected for chance-level
	weighted additive corrected ($WADD_{corr}$)	choose the option with the higher sum of cue values weighted by cue validities that are corrected for chance-level (i.e., validity-.50)
neural network	parallel constraints satisfaction model (PCS_k)	choose the option with the higher activation of the option node

Table 2: Logistic regression predicting mimicry of the rational choice model by type of intuition model, task difficulty, and mean and standard deviation of validities.

	Mimicry
Independent Variables	Odds Ratios
Task Difficulty (posterior probability)	1976.041
Mean Validities	0.003
SD Validities	4×10^{-5}
Intuition Model (control = TTB)	
EQW	0.143
$\text{WADD}_{\text{uncorr}}$	0.544
$\text{WADD}_{\text{corr}}$	1.484
PCS_1	0.660
PCS_2	2.000

Note. Intuition model is dummy-coded; Pseudo R^2 = .24.

FIGURES

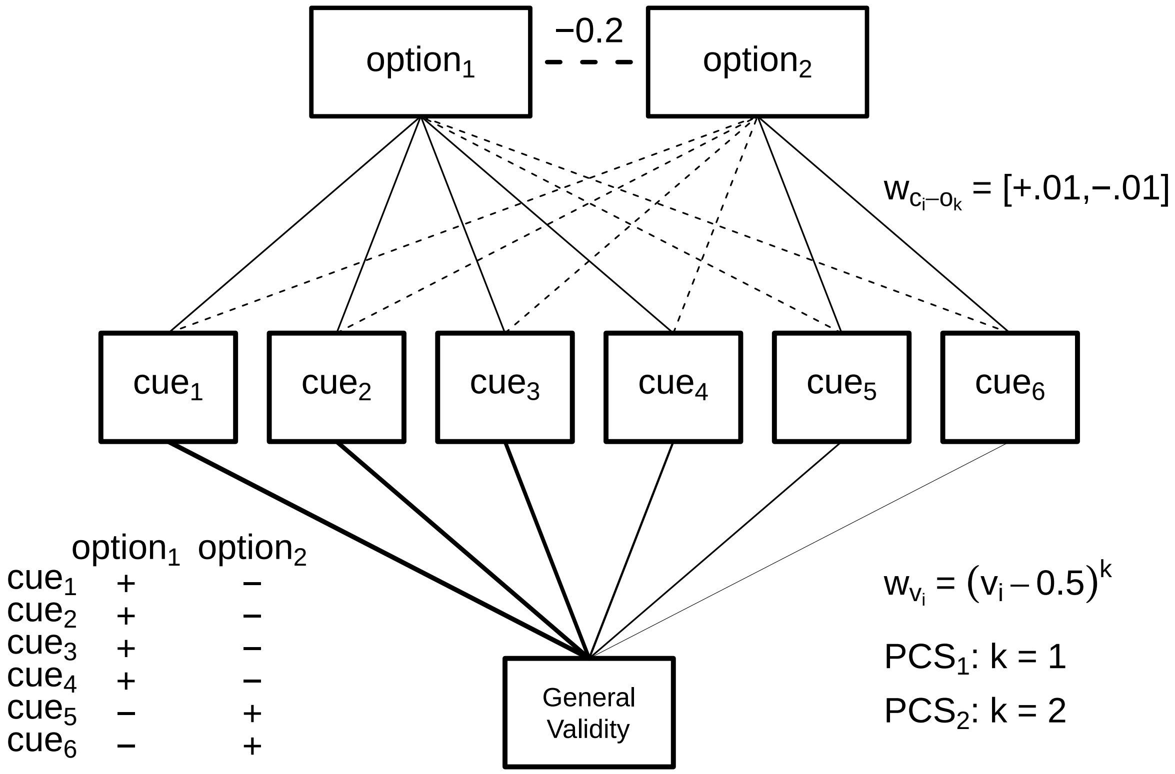
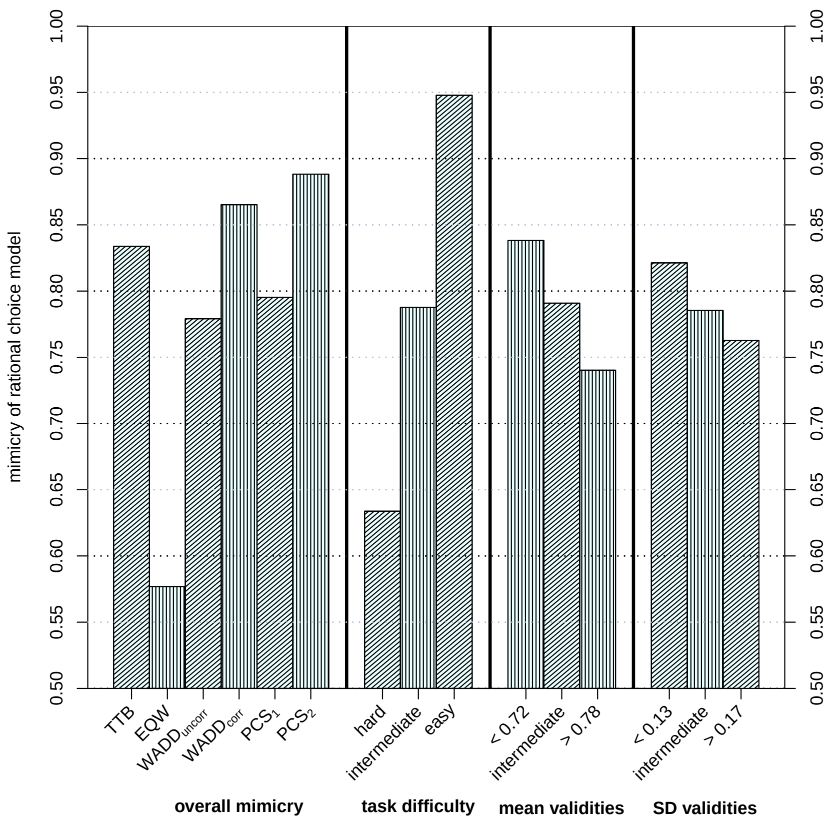


Figure 1: Exemplary task (lower left) represented in the PCS network. Cues and options are bidirectionally interconnected nodes. Cue validities v_i are transformed into weights w_{v_i} according to a transformation function (lower right) and attached to the connections between the General Validity node and the cues (linewidth indicates size of weights). (Non-)supportive cues ($-$ or $+$) are transformed into (inhibitory or excitatory) weights $w_{c_i-o_k}$ (upper right) that are attached to the connections between the cues and the options (dotted or continuous lines). Activation weighted by w_{v_i} spreads from the General Validity node into the network. Node activations are updated iteratively until changes in activation are negligible ($< 10^{-3}$). Maximum and minimum node activations are set to -1 and 1, decay is set to $.05$; see Glöckner and Betsch (2008a) for details.



Note. For hard vs. easy tasks posterior probability is < .65 vs. > .85.

Figure 2: Mimicry of the rational choice model by (from left to right panel) intuition model, task difficulty, mean validities, and standard deviation of validities.

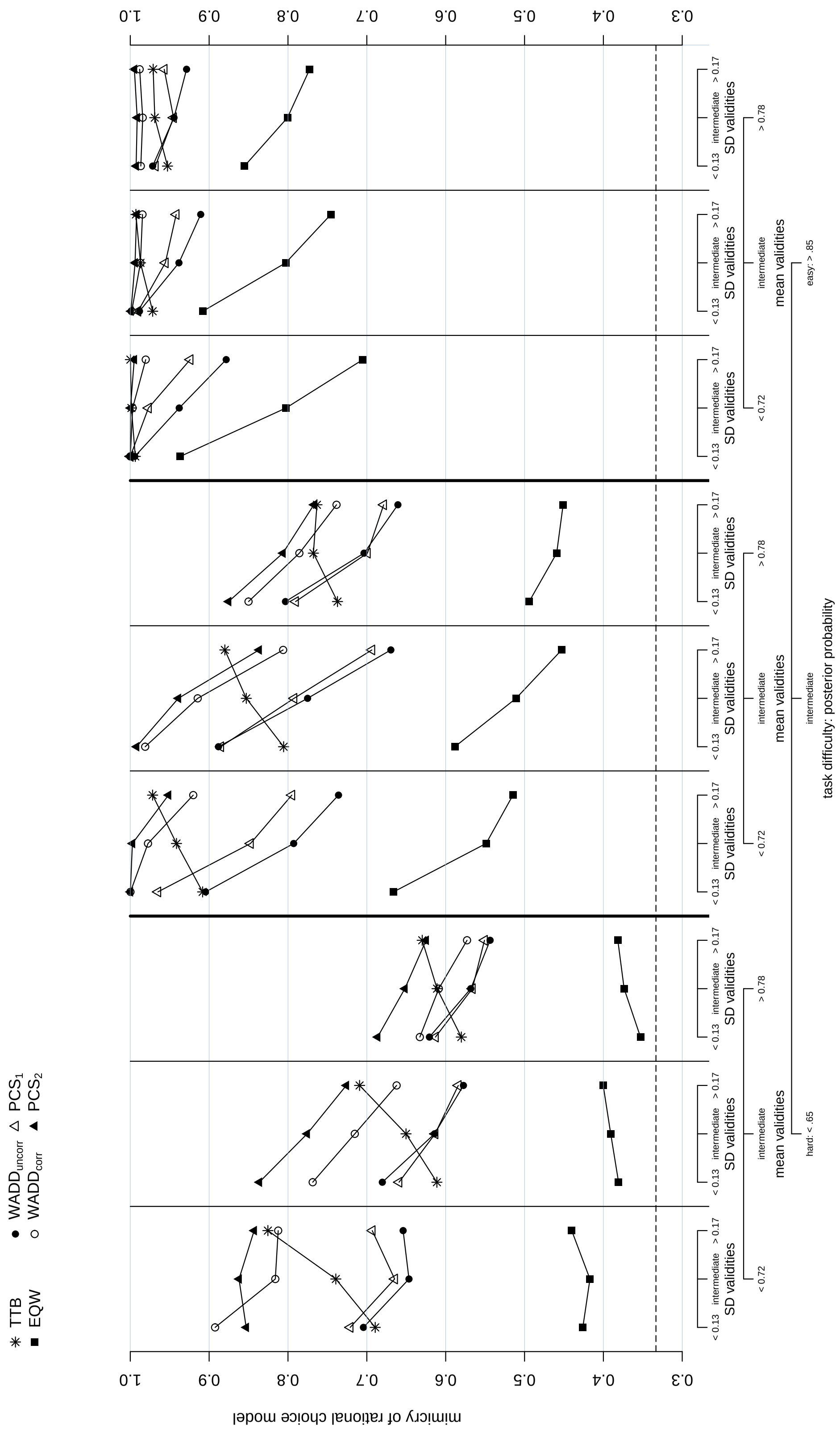


Figure 3: Mimicry of the rational choice model averaged over tasks by model, task difficulty, mean of validities, and standard deviation of validities. The dotted line at .33 indicates mimicry by chance.

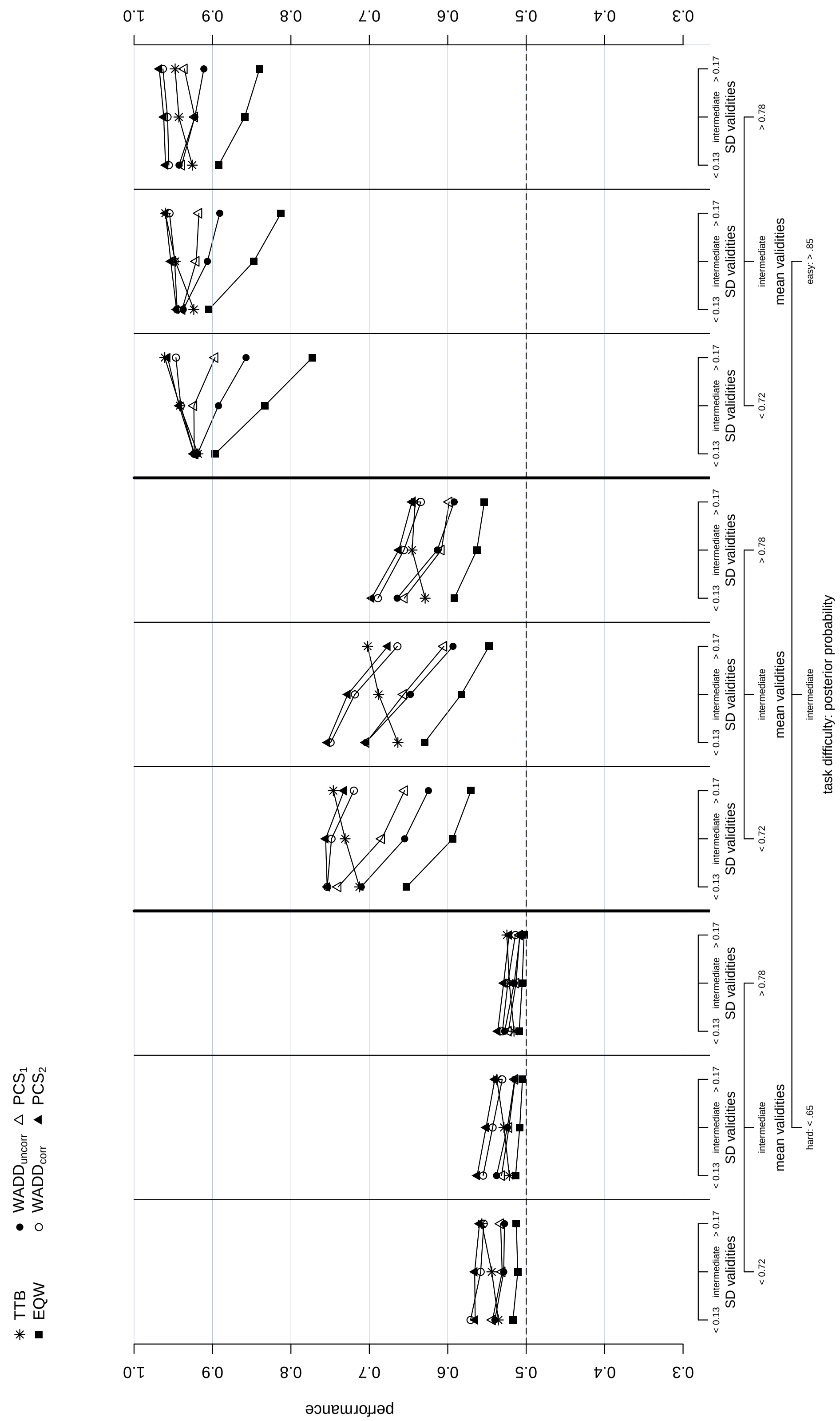


Figure 4: Expected relative number of correct decisions (performance) averaged over all tasks by model, task difficulty, mean of validities, and standard deviation of validities. The dotted line at .50 indicates chance performance.