When the Going Gets Tough: Exploring Agent-based Models of Human Performance under Demanding Conditions

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Part IV

Situation Awareness

To allow for optimal decision making, it is important for a human to have an adequate awareness of the environment, as decisions are based on the assessment of the situation. In dynamic environments humans are able to make such an assessment by constantly updating their situation awareness. As discussed in Chapter 1, situation awareness is defined by considering the three important stages perception, comprehension and projection, for which multiple cognitive processes have to be active. For example, actively maintaining information asks for working memory capacity. Also, expectations on the outcome of a specific situation or on the order of events (defined as scripts and schemas) direct the person's situation awareness. This part focuses on those aspects of cognition that are involved in a human's situation awareness and it aims at the design of models that represent a human's picture of the environment.

Chapter 8 provides a model to predict whether humans use memory or perception to obtain information from the environment. It stresses the importance of working memory in situation awareness and human performance. Next, Chapter 9 presents a model that is able to represent all three stages of situation awareness, for the purpose to be applied within a human-like agent. The model uses a mental model as a framework for relations between existing beliefs on the environment in which the agent has to perform the task. A case study is presented where the agent serves as an opponent in a flight simulation. In Chapter 10, methods are provided in order to make it possible to learn connections between beliefs within the mental model. Also, this part focuses on the support of situation awareness. Chapter 11 discusses the importance of the level of automation in maintaining situation awareness, expressed by a human's engagement to a task. It presents an automation agent that is able to support humans in order to keep their exhaustion within boundaries, while at the same time preserving their task engagement.

Chapter 8

Modeling Human Information Acquisition Strategies

This chapter is an extended version of a paper that appeared as:

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Modeling Human Information Acquisition Strategies

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Abstract. In this paper we focus on the development of a computational model that provides intelligent agents with a mechanism to decide on whether to acquire required information by retrieving it from memory or by interacting with the world. First, we present a task in which choices have to be made between acquiring information from memory or from the world. Two conditions are introduced with variable costs, and an experiment is performed to detect whether humans apply some kind of rational expected utility analysis to make this decision. Results indicate that humans do not, but instead adopt a simpler heuristic strategy. Next, we introduce a computational model that incorporates various heuristic task strategies, as well as rational ones. The human data is compared to the behavior of the model under various parameter settings. We were able to match the human actions with model actions for various task strategies, suggesting that humans differ in the task strategies they apply, and that our manner to deduce heuristic task strategies is feasible.

Keywords: Human Experimentation, Memory, Strategy Selection

1. Introduction

For the execution of almost all tasks knowledge is required. For example, making a phone call to a good friend requires – apart from procedural knowledge on how to operate a phone – explicit knowledge about the phone number. When preparing for the task, a human will make an (often implicit) choice between retrieving the required knowledge from memory, or looking it up. Intuitively, this choice is determined by the balance between the costs of looking up information on the one hand, and the costs of retrieval and the risk of mistakes on the other hand. In the phone call example the choice could be to retrieve the phone number from memory as a number of a good friend is probably easily retrievable, while the costs of looking up the required information are probably relatively high (finding the number in the address book), and the costs of mistakes are low (apologizing and calling again).

Selecting actions based on their expected costs and benefits is often described as rational decision making. However, it is well known that humans do not always follow a rational process, but often depend on heuristic approaches to solve a problem (Tversky & Kahneman, 1974; Gigerenzer, Todd & the ABC research group). In addition, humans vary (between-subject) in the task-specific strategies they apply, but this choice is influenced (within-subject) by the specific task circumstances (see, e.g., Beilock & DeCaro, 2007; Byrne, Kirlik & Fleetwood, 2008). also depends on the task use and apply different (biased) strategies depending on . For example, some people might prefer to always first try the phone number that they remember and only look it up in case of failure, even in cases in which a rational analysis would conclude that it is more efficient to look up the information.

The overall aim of our work is to build intelligent agents that exhibit human-like behavior. In order to do so, we would like to build a computational model that can decide on whether to acquire information by retrieving it from memory (information in-the-head) or by interacting with the world (information in-the-world).

In the first part of this paper, we describe the experiment in which we analyzed the behavior of humans in a relative simple task that required them to choose between in-the-head information and in-the-world information under various cost conditions. We start with a description of the task that is analyzed and that the participants of the experiment had to perform. Then, we discuss how rational expected utility analysis could be applied to the task at hand, i.e., what the types of costs and benefits of its actions are. Subsequently, the behavioral experiment and its results are presented.

In the second part of the paper, we try to align the results of the experiment with a developed task model that takes both the rational-choice approach as heuristic-based approaches into account.. The second half of the paper starts with a description of this model and the possible heuristic strategies that people could apply for the specific task that is considered in this paper. Then, the technical experiment is described in which the values for the parameters in the model are sought that best fit the results of the behavioral experiment. Finally, the implications of the findings are discussed.

2. Task Description

The computer task we developed required participants to classify presented objects to specific bins. During the task, 9 objects were presented in a sequence of 36 trials. The objects were composed of a color (red, blue or yellow) and a shape (square, circle or triangle). Each object belonged to a specific bin, numbered 1 to 9, but initially the participants did not know the correct combinations. The goal of the task was to press the number of the correct bin upon presentation of the object. On each trial participants had the option to press the number of a bin first ('choose'), or to press a button to get more information about the bins ('sense'). Participants could choose one of three buttons: button 'j' revealed the bins of objects with the same color as the presented object; button 'k' revealed the bins with the same shape; and button 'l' revealed the bin of the specific object. After the information was shown, participants had to select a bin. After a bin was chosen, the correct bin was revealed.

Participants started the task with 10 euro. Money was subtracted when either a button was chosen, or an error was made; see Table 1 for the two specific cost-settings used. In addition, for every 500 ms 0.01 euro was subtracted. A typical trial started with presenting the object with below it 9 empty boxes. Furthermore, the three buttons were shown and in the upper right corner the amount of money left.

Table 1. Costs of the two conditions.

Cond	Feature	Button Money	Button Time	Error Costs
1	*Color*	€ 0.10	1.0s = € 0.02	€ 0.10
1	*Shape*	€ 0.10	1.0s = € 0.02	€ 0.15
1	*All*	€ 0.15	1.5s = € 0.03	€ 0.20
2	*Color*	€ 0.06	1.0s = € 0.02	€ 0.12
2	*Shape*	€ 0.06	1.0s = € 0.02	€ 0.18
2	*All*	€ 0.09	1.5s = € 0.03	€ 0.24

When participants choose to sense color or shape, they had to wait for 1.0 seconds until the requested information was shown. When participants choose to sense all, they had to wait for 1.5 seconds. Meanwhile, time costs were still subtracted. When the waiting time had passed, the object was presented again with below it the 9 bins, but this time the bins were revealed that matched the specific feature that was sensed: the three bins that matched the color of the object, the three bins that matched its shape, or the bin that matched the whole object.

When a bin was chosen (immediately, or after sensing), the object and the 9 bins were presented again with the correct bin revealed. At the same time feedback was given on the choice of the participant.

Table 2. Overview of objects presented.

Feature	3 x Red	2 x Blue	1 x Yellow
3 x Circle	RC: 9x	BC: 6x	YC: 3x
2 x Square	RS: 6x	BS: 4x	YS: 2x
1 x Triangle	RT: 3x	BT: 2x	YT: 1x

The combination of 9 objects in 36 trials was determined previous to the experiment, to make sure that some objects would be often encountered so that over time it would be well known to which bin they belonged, while for others, less encountered, this could have been forgotten. See Table 2 for the number of specific objects presented over the trials.

3. Rational Expected Utility Analysis

The presented task requires interactive behavior: for its performance a mixture of elementary cognitive, perceptual, and motor operations are required. Gray and Boehm-Davis (2000) introduce interactive routines as the basis of interactive behavior. They envision interactive routines as dependency networks of low-level cognitive, perceptual, and motor operators that come together at a time span of about 1/3 to 3 seconds. Gray and Fu (2004) propose that at this time span, the human control system selects sequences of interactive routines that tend to minimize performance costs measured in time while achieving expected benefits.

For the presented task it is possible to rely to a smaller or larger degree on information in-the-world versus information in-the-head. In the first case more interaction with the world is required (button pressing), in the second case more intensive memory use (remembering the colors and shapes of the bins). Based on the specific task conditions it is expected that humans will adopt different interactive routines to minimize performance costs.

A rational strategy for performing the presented task would determine at each trial which of the four possible actions would be most optimal to execute: either directly choosing a bin, or first requesting which bins fit the color, shape, or both these aspects of the presented object. For this, a cost-benefit analysis of each action needs to be made.

For the presented task four types of costs exist: 1) the money it costs when a certain mistake is made, 2) the money it costs to press a button, 3) the time it costs to do so, and 4) the time it costs to retrieve beliefs from memory. It is possible to express all the various types of costs in money, because time costs money. It could be debated that in addition to these money and time costs another type of costs exist, namely the cognitive and perceptual-motor effort involved in executing the actions. We do not separately distinguish these efforts but assume that time is a reasonable surrogate measure for them (Gray & Fu, 2004). By doing this we also decline the minimum memory hypothesis that suggests that humans are biased to conserve cognitive resources by favoring perceptual-motor resources (Wilson, 2002). Gray, Sims, Fu and Schoelles (2006) make a convincing case that people do not favor strategies that minimize the use of memory, but those that minimize temporal cost-benefit tradeoffs.

To determine the expected utility of each of the possible actions, the expected costs for each of the four types of costs need to be determined. The money and time it costs to press one or none of the buttons depends on the task condition, but apart from that can be determined in a straightforward way. It is harder to determine the expected costs of 1) making an error and of 2) retrieving beliefs from memory.

For the first aspect the chance that one of the three possible errors is made (color false, shape false, all false) is important together with their respective, task condition dependent, penalties. The chance that a specific error is made depends on what is remembered. When it is possible to retrieve the correct bin for a specific object, the chance on any error is zero. However, when this is not possible the chance on a specific error depends on the chance of correctly retrieving knowledge concerning bins with the to-be-classified object's color or shape, but also on the chance that knowledge is retrieved that exclude specific bins from selection, increasing the chance the correct bin is picked.

The expected cost of retrieving beliefs from memory is equal to the time to do so or to the time to failure. These times, as well as the chance that knowledge can be retrieved in the first place, are important to know for calculating the expected utilities. Insight in these aspects can come from models of human memory. A well known model of memory retrieval is embedded in the cognitive theory ACT-R (Anderson, Bothell, Byrne, Douglass, Lebiere & Qin, 2004). In ACT-R declarative knowledge is presented by chunks, whose activation values determine their chance and speed of retrieval, the latter according to this formula:

$$\boldsymbol{RT} = \boldsymbol{F}\mathbf{e}^{-A_i}$$

$\boldsymbol{RT}$: The time to retrieve the chunk in seconds.
$\boldsymbol{A_i}$: The activation of the chunk i which is being retrieved.
$\boldsymbol{F}$: The latency factor parameter.

The latency factor parameter depends on the retrieval threshold, **T**, which varies substantially between ACT-R models. However, the following general relationship has been discovered: $\boldsymbol{F} = \mathbf{0.35\ e}^{\boldsymbol{T}}$ which means that the retrieval latency at threshold (when $\boldsymbol{A_i} = \boldsymbol{T}$) is approximately 0.35 seconds (Anderson et al., 2004). The full equation used by ACT-R to determine a chunk's activation takes into account several aspects, but its basis is the chunk's base-level activation. The base level activation $\boldsymbol{B_i}$ reflects the recency and frequency of use of the chunk, and is calculated by:

$$B_i = \ln\left(\sum_{j=1}^{n} t_j^{-d}\right) + \beta_i$$

$\boldsymbol{n}$**:** The number of presentations for chunk *i*.
$\boldsymbol{t_j}$: The time since the j_{th} presentation.
$\boldsymbol{d}$: The decay parameter. Standard this one is set at 0.5.
$\boldsymbol{\beta_i}$: A constant offset.

When we assume that people are able to unconsciously employ some kind of utility analysis (which includes having some kind of implicit knowledge about what they can remember, see Gray et al. (2006)) and adopt these interactive routines that minimize performance costs, we expect to find differences in behavior between the two cost conditions introduced.

4. Experiment

Sixteen first year AI students, aged between 17 and 24 years, participated in the experiment. The experiment's duration was approximate 30 minutes and participants received from 1 to 10 euro for participation, depending on their performance. In the experiment a 2-factor, between subjects design was used, with *costs* varied between participants. In condition 1, the costs of pressing a button were relatively high compared to the costs of an error, while in condition 2 the opposite was the case. For an overview of exact costs, see Table 1.

Participants started by reading a written instruction on how to perform the experiment and the costs of errors, time and sensing. Next, a practice task was given to familiarize them with the task and the costs. This task was similar to the main task, but in order to keep a low interference, color and shapes of objects were altered. Furthermore, the bin in which often or rarely encountered objects belonged and the order in which the objects were presented was altered.

4.1 Data Analysis

For data analysis we first calculated for each bin and at each trial the expected activation value of the participant's knowledge concerning the color, shape and the whole object (all) that would fit in the bin. For this we used the ACT-R formula with a standard decay of 0.5 and an offset of 0. As 'presentations' we counted the display of bin information due to button use, and the display of the correct bin at the end of each trial. Next, these activation values were used for regression analysis across participants for each trial. Trials where the activation was 0 (e.g. the object had not been presented before) were excluded from analysis.

Univariate variance analysis was used to check for differences between the two conditions. For the difference between color and shape, a repeated measure ANOVA was conducted, using the Huyn-Feldt correction. For all analysis, trials with a RT exceeding 8000ms were excluded.

5. Experimental Results

As an illustration, Table 3 shows the data of one participant (participant 9). For each trial the participant's reaction time (**RT**, the time it takes to choose a bin or button), action (**Sense**, what feature was sensed) and performance (**Correct**, which feature was correct) are shown. Overall the participants, the percentage correct ranged from 0.3 to 0.97 percent; the average percentage correct was 0.61 (*SD*=0.21). The number of times a participant chose a bin immediately ranged from 5 to 34; the average was 24.44 (*SD*=7.87). So overall, there was a wide variety in the participant's behavior.

The results of the linear regression analysis are shown in Table 4. The R^2 (explained variance), *r* (correlation) and *p*-values are given for each analysis. The results show that the activation value of color, shape and the whole object was successful in predicting a number of variables, confirming that the ACT-R theory correctly captures how human memory operates. For example, the Blue Circle in trial 13 was an object that was only shown 1 time before. Therefore, the activation value of this object was low (-1.77 on average), which coincided with the low mean percentage correct when participants immediately chose a bin (0.18).

Table 3: Experiment data of participant number 9.

Trial	Object	RT	Sense	Correct
1	BT	1370	Shape	Shape
2	RC	960	Object	Object
3	RS	1106	Object	Object
4	BC	1564	Nothing	Color
5	RC	1791	Nothing	Nothing
6	RT	923	Nothing	Shape
7	YS	1222	Object	Object
8	RC	1399	Nothing	Object
9	BS	2212	Nothing	Nothing
10	RC	800	Nothing	Object
11	RS	1766	Nothing	Nothing
12	YC	2048	Nothing	Nothing
13	BC	2783	Nothing	Shape
14	RS	1251	Nothing	Nothing
15	RC	804	Nothing	Object
16	RC	1962	Nothing	Object
17	YT	564	Object	Object
18	RS	930	Nothing	Object
19	BC	5168	Nothing	Shape
20	BS	1158	Nothing	Nothing
21	YC	2315	Nothing	Color
22	RT	1390	Object	Object
23	BC	2044	Nothing	Color
24	RC	672	Nothing	Color
25	RS	1338	Nothing	Object
26	BT	1479	Nothing	Color
27	BC	2479	Nothing	Nothing
28	YS	2415	Nothing	Nothing
29	RC	3315	Nothing	Object
30	RC	1154	Nothing	Object
31	BS	2023	Nothing	Shape
32	RT	1250	Object	Object
33	BC	3060	Nothing	Nothing
34	RS	1999	Nothing	Object
35	YC	974	Object	Object
36	BS	5372	Nothing	Shape

First_Choice (the number of participants who chose a bin immediately) is positively dependent on activation value: as activation increased, First_Choice increased. Furthermore **RT** (reaction time) was examined: RT when the object is shown for the first time (‘**RT_First**’) and the time from the presentation of the object to the moment the bin was chosen (‘**RT_Bin**’). Both RT’s are dependent on the activations: RT decreased when activation value increased. In addition, the percentage of correct classifications concerning color, shape and all was found to be positively dependent on the activation of color, shape and all, see Table 4. When the activation increased, the percentage correct increased as well. The number of times a specific feature was sensed (‘**Sense_Feature**’) for color, shape or all decreased as the activation value of that feature increased.

Table 4. Results of regression analysis.

Figure 1 shows the results of the ANOVA on the interaction between condition and feature. A trend is revealed when looking at the percentage incorrect. In condition 1 participants' percentage incorrect of shape (*M*=0.32, *SD*=0.15) was higher than that of color (*M*=0.21, *SD*=0.15; *F*(1,7)=6.81, *p*<0.04). For participants in condition 2 no such

Dependent Variables	**First_Choice**			**RT_First**			**RT_bin**		
	p	***R²***	***r***	***p***	***R²***	***r***	***p***	***R²***	***r***
Act-Color	0.002	0.27	0.52	0.000	0.48	-0.69	0.000	0.46	-0.68
Act-Shape	0.000	0.38	0.62	0.000	0.36	-0.60	0.000	0.35	-0.59
Act-All	0.001	0.35	0.59	0.000	0.53	-0.73	0.000	0.59	-0.73

Dependent Variables	**Sense Feature**			**Correct Bin**		
	p	***R²***	*r*	***p***	***R²***	*r*
Act-Color	0.002	0.28	-0.53	0.004	0.24	0.49
Act-Shape	0.000	0.40	-0.63	0.006	0.22	0.46
	0.000	0.43	-0.65	0.002	0.32	0.57

difference was found. An interaction is found between condition and feature on the number of times participants sensed a feature. For participants in condition 2 a trend was revealed, which showed that the percentage of sensed shape (*M*=0.30, *SD*=0.27) was higher than the percentage of sensed color (*M*=0.19, *SD*=0.28; *F*(1,7)=4.37, *p*<0.1). For participants in condition 1 no significant difference was found between the percentage of sensed color and the percentage of sensed shape.

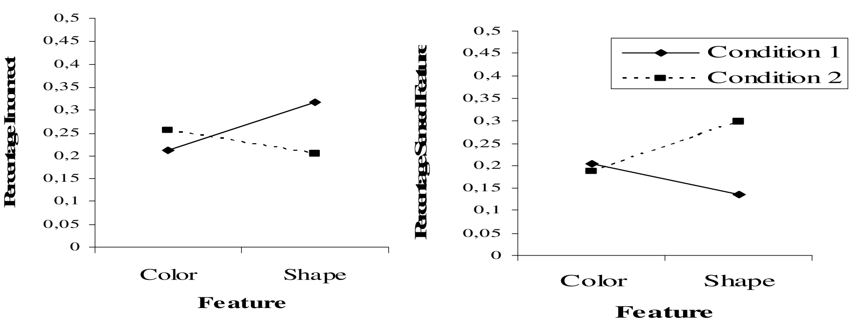

Figure 1: Interaction between feature and condition on percentage incorrect and percentage sensed feature.

Other than these interactions, no differences were found between the two conditions. This indicates that participants did not always make a rational decision, otherwise we would have expected to find more variety, e.g., in the total number of times features were sensed. Support for the thesis that humans instead rely on a prefixed strategy is found in the data, e.g., although participant 2 and 12 had the same condition, participant

2 always chose to acquire unknown information from the world (by pressing the *all* button ‘l’), whereas participant 12 always attempted to retrieve it from memory (never pressed any button).

Other support for relying in prefixed strategies can be found in the description of their approach by the subjects themselves. Table 5 gives an overview. Responses 2, 6, 8, 10 and 11 are clear examples of strategies that overrule the rational decision making.

Table 5. Strategies as described by the participants themselves.

Response	Strategy (literally translated descriptions)
1	After I knew the red circle, and a red shape was asked I choose color. Therefore I had 50% chance on a correct guess. After I stored some in my memory I was able to make a right choice for color or shape more often, thus leaving only one option because I knew that the others were different.
2	I first looked for the shapes and then I guessed, until you knew the colors many red at the left side, so use that to primary
3	Here I more often pressed “everything”
4	Guessing and memorizing, two colors (red and blue, then you also know where the yellow ones are)
5	Only after some time I got clear where the shapes were, in the beginning I had to guess and the more I saw it, the better I could guess right
6	Choosing for shape and color (“l”) if unsure or unknown, else answer
7	The first trials requesting both shape and color, afterwards only shape or color in order to have a chance of a half on a right guess (assuming that I still knew the requested objects). Initially this went quite well, but my memory is a strainer, so eventually remembering shapes and colors didn’t went very well :-)
8	My strategy was to first look at the color and then choosing between the options until I had all colors and then came the shapes by experience, again 5,45 earned.
9	My strategy was to take another bin that had the same color. The right answer became visible and could be recorded.
10	My strategy was to show everyting in the beginning. In this way I was able to see the requested bin. In this way I was able to learn quickly where what was. This worked, but had as consequence that in case of a mistake, this often was “both wrong”, because I remembered the location per combination.
11	First using the L-key (show both), until you knew more or less where is what, then gradually less the L-key and guessing the location.
12	Guessing in the beginning and remembering.
13	A mix of only color and only shape. First guessing and later you can use logical reasoning to see where is which shape. (Thus, first color, then you know e.g. that blue is in 9, then shape in the second trial and then you see that square is in 9). If you do this reasonably well you can for surely earn 7 euros.

5.1 Discussion of Experimental Results

Overall, the results show that people’s decision to acquire information from the world or from memory correlates with the activation of that information in memory following ACT-R’s base-level activation formula, and is thus dependent on the frequency and recency of using that information.

A difference is found between color and shape, in that shape appears more difficult to retrieve from memory than color. This is shown by the fact that when people retrieve information from memory, the chance of making a mistake concerning shape is higher than the chance of making a mistake concerning color, see Figure 1. When the costs of acquiring information from the world are relatively low, this difference disappears as in such a situation people request shape (button 'k') more than color (button 'j').

No other differences are found between condition 1 and 2 when looking at the participant's reaction times or actions (sense or choose bin). This indicates that the decision to rely on information in-the-world versus information in-the-head is not influenced by the specific costs of acquiring that information. Rather it seems that people make a decision based on their own (pre-)specified strategy.

This finding does not necessary conflict the hypothesis that humans optimize their interactive routines to minimize performance costs. Gray and Fu (2004) and Gray et al. (2006) only consider performance costs measured in time, and argue that humans are evolved to conserve the resource of time. For the task presented in this paper performance costs are a combination of time and money costs, and it is conceivable that humans are not good in taking into account the money costs of actions. Since the time costs of actions do not alter between the two conditions, this might explain that no more differences can be found between them. On the other hand, people definitely attempt to optimize their performance based on time and money costs. When this would not be the case and they would only optimize the time costs, they would never press a button.

6. Task Model

As mentioned in the introduction, our research goal is the development of methods and techniques that will enable intelligent agents to display human-like behavior which might be rational, but often is not. For this goal we previously developed a memory model enabling rational as well as biased reasoning (Heuvelink, Klein & Treur, 2008). This model was implemented in SWI-Prolog (Wielemaker, 2003), and incorporates ACT-R's base-level activation formula for declarative knowledge in memory. In this paper we take that model as basis for the development of a task specific model capable of executing the task previously introduced: http://www.few.vu.nl/~heuvel/CogSci-IIAModel.pl.

6.1 Execution Loop

A run of the model starts by requesting the start of the task for a specific condition and individual. This sets the current time and trial at 0 and starts the model's execution cycle by calling the *scenario_loop* clause:

```
scenario_loop :-
    current_trial(Cond, Ind, T1), retract(current_trial(T1)),
    T2 is T1 + 1, assert(current_trial(Cond, Ind, T2)),
    sense_and_form_goal,
    determine_strategy_for_goal,
    sense_and_store_result,
    scenario_end.
```

The last predicate of the scenario loop, *scenario_end,* ensures that as long as the *current_trial* is not equal to 36, *scenario_loop* keeps being called.

In *sense_and_form_goal,* the model observes the presented object, which takes time *T* as specified by *time_required_to_ observe_goal_object(Cond, Ind, T)* and stores the observed object as *goal_at_trial(classify_object(C, S), T).*

In *determine_strategy_for_goal,* the model executes a specific strategy on which we elaborate in the next section.

In *sense_and_store_result,* the model observes the correct result and stores this in its memory as *belief(color_shape, B, [C, S], T, passive_sense_result, 1.0)*, which denotes the belief that in bin *B* (1-9) color *C* and shape *S* fit. The *T* denotes the time at which this belief held, *passive_sense_result* the source of the belief and *1.0* its certainty. The fact that each belief receives a time, source, and certainty label is adapted from the memory model. In addition, the belief receives a so-called *impression_value*, which forms the constant offset of its activation level. The level of this impression value depends on whether the model chose the correct or a wrong bin. In case it was correct, the impression value *V* is equal to the *impression_value_correct_result(Cond, Ind, V)*, otherwise to the *impression_value_false_result(Cond, Ind, V).*

After any belief is stored a process of the memory model becomes active called *deduce_abstract_belief_from_belief(B).* This process deduces specific abstractions from stored beliefs with as main feature the deduction of semantic knowledge out of the episodic knowledge formed by beliefs with the introduced time, source and certainty labels. For the current task model, abstract beliefs are formed that abstract away from the T, S and C of the specific beliefs. It are exactly those abstractions that over time have multiple 'presentations' and therefore receive a high activation value.

In addition, from beliefs about the color and shape that fit in bins, beliefs are abstracted that only capture knowledge about the color, or about the shape that fits in a specific bin. This separate storage of that information is inspired by the literature that claims that features are stored independently in memory, although they are bounded by their spatial location, in our case the bins (Johnson, Wang, Zhang & Wang, 2002).

6.2 Heuristic Strategies

Gray and Fu (2004) state that the cost-benefit considerations for interactive routines only provide a soft constraint on their selection as they may be overridden by deliberately adopted top-down strategies.

We have two indications that this might have happened with participants in our task: 1) the statistical analysis did not indicate significant differences between behavior on the two task conditions which would be expected when costs-benefits of actions would have been considered; 2) participants explicitly answered the open question 'What strategy did you follow' with answers like: "When I did not know the correct answer I would pick a bin of which I knew it had the correct color." (see response 9 in Table 5).

Based on logical reasoning and inspired by the participants' answers, we came up with 37 possible strategies participants could follow. The strategies mainly differ in the number of retrieval actions humans are willing to execute, and the order in which they do so. The strategies can be classified as embedding 1 to 3 retrieval steps. There is also the possibility of an extra security check, to see whether the bin selected to be chosen is not in conflict with the given object (e.g., when checked, it turns out that the shape of the selected bin can be retrieved and conflicts that of the object). Possible actions that can be taken after one of the retrieval steps are:

- *choose a random bin (a)*
- *choose a random bin with security check (b)*
- *press show color/shape button, then choose random one of the three presented bins with security check. (c/d)*
- *press show all button, then choose that bin. (e)*

Figure 2 summarizes all strategies. In the **first retrieval step** it is tried to retrieve the bin that matches the whole object which is presented. When retrieval is unsuccessful, any one of the actions a, b, c, d and e can be taken, which results respectively in strategies 1, 2, 3, 4, 5.

Instead of directly choosing an action after unsuccessful retrieval of an object, a participant can make a **second retrieval step** to retrieve a bin of which either the color or the shape fits that of the object. If it is possible to retrieve the specific feature, that bin will be chosen. If it is not possible to retrieve the feature, again a specific action will be taken. For strategy 6 to 9 and 14 to 17, action a, b, c and e will be taken directly after an unsuccessful attempt to retrieve *color*. The difference between strategies 6 to 9 and 14 to 17 is that the latter, in case color can be retrieved, perform a security check. Strategy 22 to 25 and 30 to 33 are the same, but attempt to retrieve shape instead of color, and actions a, b, d and e are taken.

There is also the possibility of a **third retrieval step** after retrieving color or shape. That is, if color can not be retrieved, in such strategies people will first try to retrieve shape before taking an action. Strategy 10 to 13 first try to retrieve color, then try to retrieve shape. Strategies 18 to 21 do the same, but with an extra security check. Actions a, b, c and e are taken when retrieving is unsuccessful. Strategy 26 to 29 first try to retrieve shape, then try to retrieve color (strategy 34 to 37 with an extra security check). Actions a, b, d and e are taken with unsuccessful retrieval.

In addition to the 37 strategies just introduced, we also implemented the rational strategy and included it as strategy 38-40. These strategies were equal in their determination of the expected costs of each action, but varied in the time it took them to introspect the activation values of the beliefs. This took them respectively 10, 15 and 20% of the time that it would take to actually retrieve the belief inspected.

In case a strategy would lead to action a: choice of a random bin, any of the nine bins could be chosen. Although the model would select one of these options, all of them were denoted as possible chosen bins. Similarly for action b: all the random bins of which no conflicting information could be retrieved were denoted as possible chosen bins.

When action c, d, or e was selected, the bins that fitted the requested information were revealed, and this knowledge was stored. The impression value of the stored information dependent on the feature sensed, as denoted by *impression_value_sense_color/shape/all_bin* respectively. Also from these specific beliefs about the color, shape or color-shape of bins, abstract beliefs were deduced. Next, (one of) the revealed, non conflicting bin(s) was chosen, and the possible bins that could have been chosen denoted.

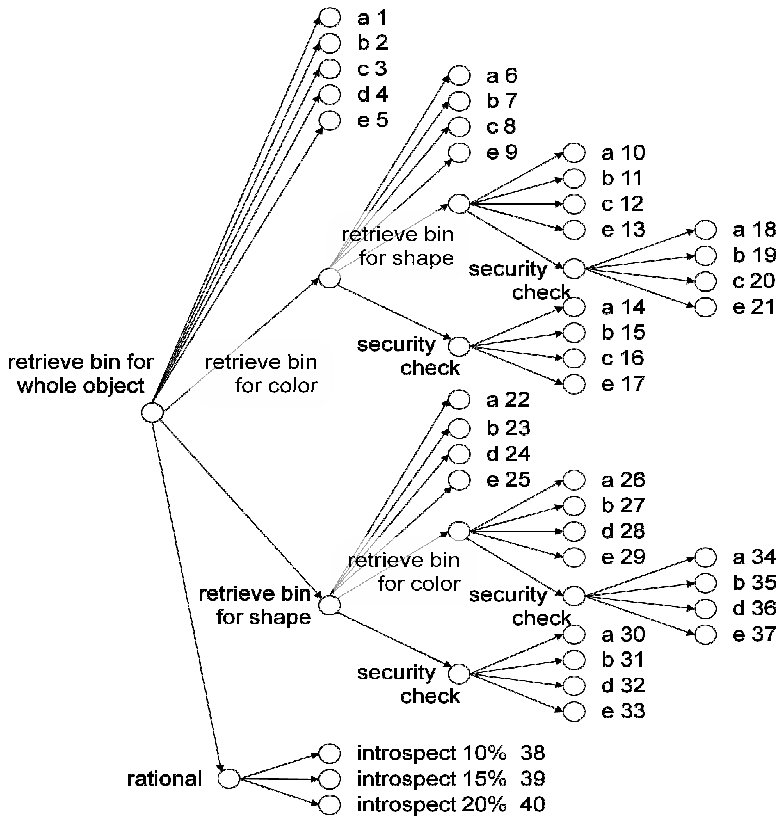

Figure 2: Schematic overview of all strategies.

7. Parameter Fitting

The model as described above contains a large number of parameters. Each specific parameter setting will result in different behavior of the model. To answer the question to what extent the model can correctly describe human behavior, we performed a technical experiment with which we tried to find parameter settings for which the model displays behavior close to that of a participant.

Unfortunately, due to the large number of parameters, we were unable to fit them all. For the current research we focused on fitting the various strategies as well as the specific parameters that influence the storage and retrieval of beliefs. This means that the parameters that influence the time to sense information and to execute actions were fixed. In specific, we fixed the following parameters to the given values, based on inspection of the empirical human data:

time_required_to_observe_goal_object(_,_, 0.3)
time_required_to_press_button(_,_, 0.4)
time_required_to_press_bin(_,_, 0.7)

The technical experiment has been performed as follows. First, we analyzed the empirical human data further to find realistic ranges for the parameters in the model. This resulted in the following parameters that were run:

impression_value_sense_color_bin:	*0.0, 0.1, 0.2*
impression_value_sense_shape_bin:	*0.0, 0.1, 0.2*
impression_value_sense_all_bin:	*impression_value_sense_shape_bin + 0.0, 0.2*
impression_value_correct_result:	*0.0, 0.1, 0.2*
impression_value_false_result:	*impression_value_correct_result + 0.0, 0.2*
retrieval_threshold:	*-1.0, -0.7, -0.4, -0.1, 0.2, 0.5*
strategy:	*1, 2, …, 39, 40*

As can be seen, we decided to separately denote the *impression_value* that a belief about the color, shape, or color and shape of a bin would receive after sensing color, shape or both, respectively. This way it is possible for a possibly existing difference in how well color and shape are remembered to show up. Due to the large number of parameters already present we decided not to parameterize the impression value given to the abstract beliefs about the color or shape of a bin that were deduced from beliefs about its color and shape. Therefore, differences between the storage of color and shape could only show up in case the model selects the sense-color and sense-shape button.

In addition, we decided to make the *impression_value* of *sense_all_bin* dependent on (equal or larger to) the *sense_shape_bin*, and the *impression_value* of a *false_result* dependent on (equal or larger to) that of a *correct_result*. The reason we did this is that the impression value denotes the amount of attention paid to the information to be remembered. We gathered it illogical that one out of three features would receive more attention than one out of two, or that a correct, probably expected, result would receive more attention than a false, important to remember, result.

Next, we used the model to run simulations for all the possible combination of the introduced parameter settings. This meant that we ran the model 27,864 times (twice for strategies 38-40 due to the influence of the task condition), each time giving the model the same 36 objects to classify as were given to the participants. For all parameter settings and at each trial the following information was logged: the action executed by the model (sense-color, sense-shape, sense-all or none), its reaction time (RT, the time until the button, or in case of 'none' the time until a bin number was pressed), and the possible bins the model could have chosen.

Subsequently, we compared each participant with the 27,864 simulation results. To do this in a structured way, we developed a distance measure that calculates for each trial a distance between the model data and the data of the participant. For this, we first calculate a distance value for each aspect, in case of reaction time *RT* by the following formula:

*distance_RT = Abs(human_RT - model_RT) / (2 * SD)*
SD: the standard deviation of the human reaction times.

For the *chosen bin*, the distance was 0 when the human had chosen a bin which was one of possible the bins the model could have chosen, and 1 otherwise. For *action*, the distance was calculated according to Table 6.

Table 6: The distance measure for actions.

Action	**Color**	**Shape**	**All**	**None**
Color	0	1	0.5	0.5
Shape	1	0	0.5	0.5
All	0.5	0.5	0	1
None	0.5	0.5	1	0

For the overall distance measure we decided to let the similarity between the human action and model action have the strongest influence, followed by the similarity of the bin in which the object is classified, while the reaction time only has a slight influence:

$$distance = (6 * distance\_action + 2 * distance\_chosen\_bin + distance\_RT\ ) / 9$$

The reason for this measure was that the use of different strategies, which is the focus of this paper, mainly shows up in the action choices. In addition, we did not expect to find very good fittings for the reaction times due to the fixing of the *time_required_to* parameters that largely determine the model's reaction times.

7.1 Results Parameter Fitting

The results of the parameter fitting for four different participants will now be discussed. Although this is not yet a thorough validation of the model, it provides evidence for the feasibility of the model. The subjects, two for each condition, were selected based on typical behavior patterns: participant 2 (condition 2) almost always requested information, participant 7 (condition 1) almost never did. Participant 9 (condition 1) and 10 (condition 2) were chosen because they seemed to perform rational behavior (more sensing in the beginning, less sensing at the end). Table 7 shows the actions of the four participants.

Table 7. Sense actions of the 4 participants.

Object	**PP2**	**PP7**	**PP9**	**PP10**
1. BT	Object	Color	Shape	Color
2. RC	Object	Color	Object	Shape
3. RS	Object	Nothing	Object	Shape
4. BC	Object	Nothing	Nothing	Shape
5. RC	Object	Nothing	Nothing	Nothing
6. RT	Object	Nothing	Nothing	Color
7. YS	Object	Nothing	Object	Shape
8. RC	Object	Nothing	Nothing	Nothing
9. BS	Nothing	Nothing	Nothing	Nothing
10. RC	Nothing	Nothing	Nothing	Nothing
11. RS	Object	Nothing	Nothing	Nothing
12. YC	Object	Nothing	Nothing	Shape
13. BC	Object	Nothing	Nothing	Nothing
14. RS	Object	Nothing	Nothing	Nothing

15.	RC	Object	Nothing	Nothing	Nothing
16.	RC	Nothing	Nothing	Nothing	Nothing
17.	YT	Object	Nothing	Object	Shape
18.	RS	Object	Nothing	Nothing	Nothing
19.	BC	Object	Nothing	Nothing	Shape
20.	BS	Object	Nothing	Nothing	Nothing
21.	YC	Object	Nothing	Nothing	Nothing
22.	RT	Object	Nothing	Object	Shape
23.	BC	Object	Nothing	Nothing	Color
24.	RC	Object	Nothing	Nothing	Nothing
25.	RS	Object	Nothing	Nothing	Nothing
26.	BT	Object	Nothing	Nothing	Color
27.	BC	Object	Nothing	Nothing	Nothing
28.	YS	Object	Nothing	Nothing	Shape
29.	RC	Object	Nothing	Nothing	Nothing
30.	RC	Nothing	Nothing	Nothing	Nothing
31.	BS	Object	Nothing	Nothing	Nothing
32.	RT	Object	Nothing	Object	Color
33.	BC	Object	Nothing	Nothing	Shape
34.	RS	Object	Nothing	Nothing	Nothing
35.	YC	Object	Nothing	Object	Shape
36.	BS	Nothing	Nothing	Nothing	Nothing

The lowest distance values of subjects 2, 7, 9 and 10 are 5.242, 2.105, 5.555 and 6.340 respectively. For all participants the settings with distance values that lie within 1% of this lowest distance value were analyzed. This resulted in only 1 setting for participant 10, but 7, 18, and 16 different settings for subjects 2, 7, and 9 respectively. We found that the parameters for *strategy* and *retrieval_ threshold* were equal across the settings per participant, but that the *impression_values* strongly fluctuated per setting. This, however, is not surprising as differences stemming from the setting for, e.g., *impression_value_sense_color_bin*, only show up in case this sense action is actually selected.

The strategy parameter that fits participant 2 is strategy 5, with a retrieval threshold of 0.5. This strategy entails that when an object can not be retrieved from memory, its position will be requested. Because the model's retrieval threshold is very high (0.5) the objects' activation values frequently lie below the retrieval threshold. Therefore, the model is often unable to retrieve the presented object, and thus often (30x) requests information. This represents the choices of participant 2, who 31 times pressed button 'l': sense-all. Looking at Table 7, it appears that the participant could only remember the frequently presented red circle, and the blue square. Analysis of the best matching setting pointed out that action of subject 2 indeed correlates with action of the model (r=0.47, p<0.01). Reaction time of subject 2 does not correlate with reaction time of the model.

Strategy 30 and a retrieval threshold of 0.5 fit best with participant 7. This strategy often results in directly choosing a bin as when shape can not be retrieved, a random bin is chosen. This is apparent in participant 7, who only pressed a button at the first two trials. The relatively low distance (2.103) follows from the fact that when the model chooses a random bin, the bin chosen by the participant always matches the possible chosen bins of the model. No significant correlations were found between model RT and human RT and between model action and human action. This is partly due to the fact that the values of model RT and model action varied little and not at all, respectively.

Participant 9 fits best with strategy 39 and a retrieval threshold of -0.1. Strategy 39 is a rational strategy taking the costs of acquiring information from the world and from memory into account. Since this participant had been assigned the condition in which the button costs are high and penalties low, such a strategy would result in a pattern that the only time information will be acquired from the world is when the chance or error is really large, e.g., for an object rarely encountered. This behavior is indeed shown in participant 9, see Table 3. For example, on trial 17 a Yellow Triangle was presented, an object which was never presented before, and that was one of the few (7) trials the participant decided to press the sense-all button. Further analysis revealed a significant correlation between human action and model action (r=0.68, p<0.01), but also between human RT and model RT (r=0.40, p<0.02).

Strategy 36 and a retrieval threshold of 0.2 fit best with participant 10. Strategy 36 is, contrary to our expectations, not a rational strategy. The strategy either results in choosing a bin (when either shape or color is known), or in sensing the shape (when shape and color are both unknown or one of them conflicts). The choices of participant 10 reveal such a pattern as the participant's actions are mainly to directly choose a bin or to sense shape. This is confirmed by the significant correlation between human action and model action (r=0.61, p<0.01). In addition, a trend in correlation was found between human RT and model RT (r=0.31, p<0.1).

8. Discussion & Conclusion

The results show that it was possible to find parameter settings that matched reasonably well with the four investigated participants, especially on the executed actions. Reaction time proved to be a less optimal measurement for parameter fitting. This could be due to the fact that we set a fixed time to observe information, and to press a bin or a button for all participants. As reaction time is personal, such parameters need to be fitted as well.

We can also conclude that people adopt different strategies to decide whether to acquire information in-the-world versus information in-the-head. At this moment we think that many of our participants already had decided on how to act, instead of deciding this on-line. The descriptions of the strategies as listed in Table 5 support this hypothesis.

With hindsight knowledge, we can make a few critical remarks about our experimental setup and our model. First, the task that was given to the subjects was too complex, in the sense that it contained too many cost parameters. This made it difficult for the participants to do an accurate cost-benefit analysis, shown by the fact that we were not able to clearly distinguish an effect of the different cost conditions. It is interesting to find out whether this would be different for tasks that are less complex and involve fewer actions to consider. In such a situation the effect of costs of information acquisition actions and costs of errors can be studied more closely.

Second, it became clear that the setup of the task made it possible to choose a strategy that optimizes the utility *over different trials.* Some participants preferred to sense 'color' or 'shape' over 'both' because the first two options revealed information about objects in three bins instead of information about an object in one bin (e.g., see response 13 in Table 5). As the rational strategies in our model do not take this into account, such strategies won't fit to a rational strategy in the model, although they actually are rational.

This could also explain why the behavior of participant 10, which appeared rational, did not fit best with a rational strategy (see the previous section).

Third, we can conclude that we made a suboptimal choice in selecting the parameters to be fitted. Major parameter settings were fixed (time to observe information and time to execute actions) while it was attempted to fit others (impression-values of sensed information) that were of much less importance to task execution.

Fourth, it is a question whether our 'meta-model' for deriving the 37 strategies is correct, i.e., the idea that the heuristic strategies vary in the number (and order) of retrieval actions humans are willing to take to come to a decision. The rational strategy decides by (unconsciously) considering all the possible retrieval and sense actions and their effects at the same time. The heuristic strategies execute a more serial process; they execute a retrieval action, and then decide on what to do next, which could be further deliberation.

The modeling of these different approaches to decide on what to do resembles the work of Dickison and Taatgen (2007), who state that for complex tasks it may become impossible to model individual differences by parameter tuning. Instead, they propose that people differ in the control strategies they employ, and that these manifest themselves as different problem-solving strategies. These control strategies supposedly differ in the amount of top-down control exerted on behavior, opposed to this behavior being driven by bottom-up processes.

It could well be that people differ in the type of control they exert (with top-down control leading to more rational behavior) based on other individual differences, e.g. the capacity of their working memory (WM). Differences in WM capacity have been used to explain the differences between the task strategies selected by different humans under the same task circumstances, as by the same human under different circumstances (Beilock & DeCaro, 2007). Given these findings, we think that our approach to capture varied human decision-making by modeling (heuristic) strategies that vary in the number of retrieval actions humans are willing to make, is a feasible one.

In future work, we would like to redo the experiments using the insights that are described above, i.e., using a simpler task. In addition, we want to vary the various *time-to-do-x* parameters and to fit the model on these parameters as well. Moreover, we would like to extend the model so it does not executes a pre-determined strategy, but on-line selects one, e.g., based on the available WM capacity. Furthermore, it might be useful to do a separate experiment with a simple task to further investigate the difference we found between the retrieval of color and shape.

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