Supplementary Materials for Chapter 5: Thirty-Nine ACT-R Models of Decision Making

5

Chapter

Supplementary Material A: Parameter Settings

All 39 ACT-R decision models assume that memory, motor, and perceptual processes interweave with decision processes. In modeling these processes, we had to set the values of a number of parameters (see Table 5.A1). All parameters were fitted by using participants' data from Experiment 1.

Parameters Determining the Time for Retrieval Failures: τ, F

The time to decide that a chunk (representing an unknown city or cue value) cannot be retrieved is determined by the retrieval threshold, τ, and the latency factor, F (Equation 5.8). Following the principle of constrained modeling, we set these parameters by creating a separate ACT-R model of recognition, labeled *ACT-R recognition*, which we fitted to participants' responses in the recognition task of Experiment 1 (the model code is available at http://www.ai.rug.nl/~katja/models). Specifically, we let the model solve the recognition task in the same way the human participants did, by presenting each city name (one at a time) and letting the model indicate whether the name could be retrieved. As it turns out, in this task participants judged cities about 120 ms faster as recognized (*Mdn* = 962 ms) than as unrecognized (*Mdn* = 1,081 ms); for simplicity, in computing the medians, we collapsed the data of all participants, following our analyses of the data from the decision task, as well as Pachur, Bröder, and Marewski's, (2008) original analyses. We were able to fit this difference in time (after informally searching the parameter space) by adjusting the retrieval threshold, τ, to -.3 and the latency factor, F, to .1. We then made ACT-R recognition the recognition component of the 39 decision models.

Parameters Determining the Time for Successful Retrievals: n, t_n, d, W_j, S_{ji}, S, s

The time to successfully retrieve a chunk (representing a recognized city or its cue value) is determined by the activation of the chunk in memory, A_i, and by the latency factor, F (see Equation 5.7). We fixed the latency factor, F, on retrieval failure times (i.e., the time it takes to judge an alternative's name as unrecognized) as described in the preceding paragraph. The activation, A_i, of a chunk i is influenced by three components: its base-level activation, B_i, spreading activation, S_i, and a noise component, ε (see Equation 5.1). We estimated the parameters for the base-level activation, B_i, and the spreading activation, S_i, by using the data from the cue memory task of Experiment 1. In the cue memory task, participants were asked to recall the cues of each of the six cities from the learning task. As it turns out, positive cues were recalled about 80 ms faster than negative cues (positive cues: *Mdn* = 1,148 ms, negative cues: *Mdn* = 1,234 ms); for simplicity, in computing the medians, we collapsed the data of all participants, following our analyses of the data from the decision task, as well as Pachur et al.'s, (2008), original analyses. In ACT-R, such a difference in retrieval time can be explained by assuming a difference in activation, A_i,

Table 5.A1 Parameter Settings.

Parameter	Explanation	Value	Method by which the parameter was set	Parameter used for[a]
Parameters Determining the Time for Retrieval Failures				
τ	Retrieval threshold	-.3	Fit to data from recognition task	Retrieval failure time (Equation 5.8)
F	Latency factor	.1	Fit to data from recognition task	Retrieval failure time (Equation 5.8)
Parameters Determining the Time for Successful Retrievals				
n	Number of presentations of a chunk i	(I) 3,000,000 (II) 60,000 (III) 50,000 (IV) 30,000	(I and II): Fit to data from cue memory task (III and IV): Fit to data from decision task	Base-level activation B_i (Equation 5.2)
t_n	Time in seconds since the first presentation of a chunk i	$-1e^{10}$	Fit to data from cue memory task	Base-level activation B_i (Equation 5.2)
d	Decay parameter	.5	Value that is typically used (Schooler & Hertwig, 2005; Anderson & Lebiere, 1998)	Base-level activation B_i (Equation 5.2)
W_j	Activation of a chunk j in the imaginal buffer	(number of chunks j in the imaginal buffer)$^{-1}$	ACT-R default	Spreading activation S_i (Equation 5.3)
S_{ji}	Associative strength between chunks j and i	(I) Equation 4 determines values[b] (II) 0	(I) Calculated using Equation 4 (II) Fit to data from cue memory task	Spreading activation S_i (Equation 5.3)
S	Maximum associative strength	3	Fit to data from cue memory task	Associative strength S_{ji} (Equation 5.4)
s	Value determining the amount of retrieval noise	.2	Value that has been used in the literature (e.g., Taatgen, et al., 2008)	Retrieval noise ε (Equation 5.5)
Other Parameters that Affect Timing				
m	Value determining the amount of perceptual and motor noise	3	ACT-R default, if noise is switched on	Perceptual and motor noise
visual-attention-latency	Time in seconds to shift visual attention	.035	Fit to data from decision task	Moving attention
imaginal-delay	Time in seconds to respond to imaginal request	.1	Fit to data from decision task	Updating of the imaginal buffer

Note. (I) = for cities and positive cues; (II) = for negative cues; (III) = for the big chunk in the Model 4.H and 1&4.H classes; (IV) = for the big chunk in the Model 4.L and 1&4.L classes. [a] For simplicity we listed all parameters only once in the table. However, some parameters are used in more than one equation. For instance, the latency factor, F, is used for calculating the time for retrieval failures and for successful retrievals. [b] There is no single value; S_{ji} are calculated using Equation 5.4 for cities and positive cues values.

between positive and negative cues. Using Equation 5.7, we first calculated the difference in activation, A_i, that would be necessary to cause such a difference in retrieval time. As described in detail below, we then estimated the values of parameters determining the base-level activation, B_i, and spreading activation, S_i, such that the previously calculated difference in activation, A_i, would emerge.

A chunk's base-level activation, B_i, reflects the cognitive system's previous experience with the chunk. The recognized cities in Pachur et al.'s (2008) experiments were not only well-known British cities but these cities and their values on the three cues (industry, soccer and airport) were also extensively practiced in the learning task. In setting the base-level activation, B_i, we therefore assumed that the cities and their cue values would be strongly activated and, for simplicity, that this activation would be identical for cities and positive cues. To model the difference in retrieval times between positive and negative cues, we assumed that negative cues have a lower base-level activation, B_i, than positive cues. The exact values of base-level activation, B_i, depend on the values of three parameters: n, t_n, and d (Equation 5.2). Setting d at .5, a value that is typically used in the literature (e.g., Anderson & Lebiere, 1998; Schooler & Hertwig, 2005), we estimated the values of t_n (the first encounter with the chunk) to -1e10 seconds and n (the frequency of encounters) to 3,000,000 for positive cues and 60,000 for negative cues.

In addition to chunks representing cities and cue knowledge about the cities, Models of the 4 and 1&4 classes assume a chunk representing implicit knowledge about a city's size, labeled big chunk, b. To set the base-level activation of the big chunk, we kept d and t_n at the values described in the previous paragraph (i.e., $d = .5$; $t_n = -1e10$) and estimated n. To estimate n, we fit the Models of the 4 and 1&4 classes to the human data in the decision task. More precisely, we first estimated n for what we now call Model 4.H by fitting this model to the cue groups' decision data. In doing so, we estimated n to be 50,000, resulting in a base-level activation (B_b,= -.003) slightly above the retrieval threshold of -.3. As Model 4.H had difficulties to fit the spread of the decision time distributions, we then build the race version of this model. After realizing that this race version (i.e., Model 1&4.H) fit the decision times, but overestimated the proportion of choices for the recognized city in the decisions, we decided to re-fit n. Specifically, we examined how well a race version of Model 4 (i.e., Model 1&4) would fit the cue group's decisions, if n was set to a lower value. After trying out various values for n, we settled on a value that yielded a good fit of the decisions, and called the race model with the new value for n Model 1&4.L. In this model, n was set to be 30,000, resulting in a base-level activation, $B_b = -.51$, slightly below the retrieval threshold of -.3. Once n was estimated for Model 1&4.L, we then – for the sake of completeness – additionally created the non-race version of Model 1&4.L, that is, Model 4.L, which assumes the same value for n as Model 1&4.L.

The amount of spreading activation, S_i, from a chunk j in the imaginal buffer to a chunk i in memory is determined by the strength of activation of j in the imaginal buffer, W_j, and by the associative strength, S_{ji}, between j and i (Equation 5.3). For calculating the strength of activation in the imaginal buffer, W_j, we used ACT-R's default settings (1/number of chunks in the buffer). In setting the spreading activation, S_i, for positive and negative cues (see above, beginning of this section), we varied the associative strength, S_{ji}, between positive and negative cues: The associative strengths, S_{ji}, between positive cues and cities were calculated using Equation 5.4, where we fit the cue memory data by setting the value of Equation 5.4's free parameter S (i.e., the maximum spreading activation) to 3, after informally searching the parameter space. The associative strengths, S_{ji}, between negative cues and cities were set to 0, as this setting allowed us to generate a sufficiently large difference in activation, A_i, between positive and negative cues. In the Model 4 and 1&4 classes, also the associative strengths, S_{ji}, between positive cues and the big chunk were calculated using Equation 5.4 with the same value for Equation 5.4's free parameter S (= 3).

The amount of retrieval noise, ε, that is added to a chunk's activation when the chunk is requested for retrieval is determined by the parameter s (Equation 5.5). As ACT-R does not provide a default value for this parameter, we set it to .2, which is a value that has been used in the literature before (e.g., Taatgen, Huss, Dickison, & Anderson, 2008).

To assess the adequacy of our parameter settings for the base-level activation, B_i, spreading activation, S_i, and retrieval noise, ε, we constructed a separate ACT-R model for the cue memory task, labeled *ACT-R cue_retrieval_PN*. As the human participants, this model had to indicate for each city-cue combination, whether the cue value was positive, negative, or unknown. Using the parameter values described above (see also Table 5.A1), this model was able to fit the difference in decision times between positive and negative cues. We made ACT-R cue_retrieval_PN the cue-retrieval component of those decision models that retrieve positive and negative cue values before their decision (i.e., all PN variants of the Model 2, 3, 4, 5, 1&3, 1&4, and 1&5 classes, respectively). Keeping the parameters fixed, we then generated a second model, *ACT-R cue_retrieval_P*, which can only retrieve positive cue values. We made this model the cue-retrieval component of those decision models that retrieve only positive cue values before their decision (i.e., all P variants of the Model 2, 3, 4, 5, 1&3, 1&4, and 1&5 classes, respectively). The codes for both cue retrieval models are available at http://www.ai.rug.nl/~katja/models.

Other parameters that affect timing: *m*, visual-attention-latency, imaginal-delay

In addition to the parameters described above, ACT-R has a number of other parameters that affect the timing of actions. We left those parameters at their default values, with three exceptions: the setting of perceptual and motor noise, the time required for moving attention to a stimulus on the screen, and the time required to update the imaginal buffer.

Perceptual and motor noise, *m*

ACT-R comes with a mechanism for adding noise to the timing of perceptual or motor actions. Whereas this mechanism is turned off by default, we decided to turn it on, because it seemed highly unlikely to us that the timing of perceptual and motor actions would be free of variability (for similar assumptions, see Gunzelmann, Gross, Gluck, & Dinges, 2009; Trafton, Altmann, & Ratwani, 2009). Once turned on, the mechanism adds noise to the timing of the visual and manual modules. This mechanism has one free parameter, m, which we left at its default value, 3.

Visual-attention-latency

By default, ACT-R assumes that people will move their attention to the locations on a computer screen where they detect a change on the screen. For example, in different experimental trials a stimulus might appear at different locations on the screen, leading people to move their attention to the stimulus's new location in each of the trials. In the decision task we used, the cities were always presented at the same location on the screen. Thus, participants knew exactly where to look. To take this into account, we reduced the *visual-attention-latency*, that is, the time it takes our models to move their attention, from 85 ms (default value) to 35 ms.

Imaginal-delay

The imaginal buffer holds information that is currently in the focus of attention (e.g., a city name or a cue). When new information becomes available (e.g., a new cue has been retrieved), the information in the imaginal buffer needs to be updated (Borst, Taatgen, & van Rijn, 2010). By default, this update (called the *imaginal-delay*) takes 200 ms, but the duration varies among the ACT-R models reported in the literature (see e.g., Anderson & Qin, 2008, who sampled the duration from a random distribution between 0 and 1500 ms). In the decision task we used, the update of the imaginal buffer is relatively simple, because information does not need to be replaced (e.g., as in Borst et al.) but is only added until a decision is made. For instance, if an additional cue has been retrieved, then this cue does not need to replace previously retrieved cues and city names but can just be added to the imaginal buffer. To take the simplicity of our task into account, we reduced the time it takes to update the imaginal buffer to 100 ms.

Supplementary Material B: Further Illustration of the Race Models

Below, we explain the race models in more detail. Recall, that the race models were generated by partially combining the Model 1, 3, 4, and 5 classes with each other, resulting in the Model 1&3, 1&4, and 1&5 classes. As all models, each race model exists in a version that uses positive and negative cues (*PN* in the model name) and a version that only uses positive cues (*P* in the model name). For simplicity, below we outline the PN versions. Note, however, that the P versions are identical to the PN versions, with the only difference being that the P versions cannot retrieve and use negative cues. Additionally, for each race model we implemented a version that assumes that retrieved cues will at times be forgotten (*F* in the model name). For simplicity, below we outline the versions of the models that do not forget cues. However, note that the forgetting versions are identical to the non-forgetting versions, with the only difference being that as soon as at least two cues have been retrieved, the forgetting process will be added to the race. If the forgetting process wins the race, all cues that have been retrieved up to that point will be "forgotten" and the race between responding with the recognized city and retrieving and encoding cues starts again. Finally, note that for each race, all processes that compete in the race have an equal likelihood to win the race (see Footnote 8 in the main text of Chapter 5).

The 1&3 race Model class reflects the assumption that, while decisions will exclusively rely on recognition (as in Model 1), occasionally cues about the recognized city are retrieved (as in the Model 3 class). Figure 5.B1 shows the different processes that race against each other at each possible step in the decision process of Model 1&3.PN. To illustrate this, assume Model 1&3.PN is presented with a pair of cities. After assessing recognition of the cities, a race between responding directly with the name of the recognized city (respond recognized) and retrieving and encoding one of the three cues (retrieve industry, airport, or soccer) takes place. This race is repeated either (a) until the model responds with the recognized city before all three cues are retrieved, or (b) until all three cues are retrieved and encoded and a decision is made in favor of the recognized city.

The race models of the Model 1&4 classes reflect the assumption that decisions can be based on recognition (as in Model 1), as well as on an implicit use of cues (as in the Model 4 classes). Figure 5.B2 shows the different processes that race against each other at each possible step in the decision process of Model 1&4.L.PN. In this model, the race between different processes is repeated either (a) until the model responds with the recognized city before all three cues are retrieved, or (b) until all three cues are retrieved and encoded and a decision is made in favor of the recognized city, or (c) until all three cues are retrieved and encoded and the model attempts to retrieve the big chunk. Once the process to retrieve the big chunk wins the race, the model's decision will depend on the encoded cues via implicit, subsymbolic spreading activation.

The race models of the Model 1&5 classes reflect the assumption that decisions can be based on recognition (as in Model 1), as well as on an explicit use of *D* cues, with *D* reflecting the decision criterion of the model (as in the Model 5 class). Figure 5.B3 shows the different processes that race against each other at each possible step in the decision

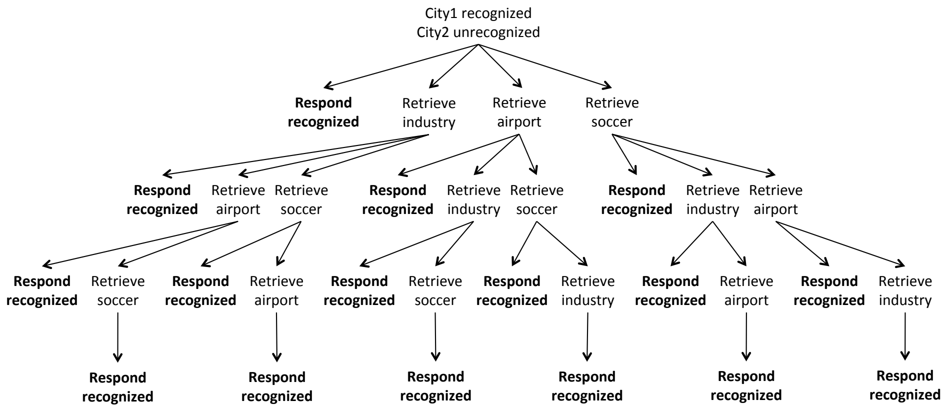

Figure 5.B1 Illustration of the race between different processes in Model 1&3.PN. As can be seen, the process to decide with the recognized city races against the retrieval of not-yet-retrieved-cues up to three times. Once all three cues have been retrieved, the decision will be made in favor of the recognized city.

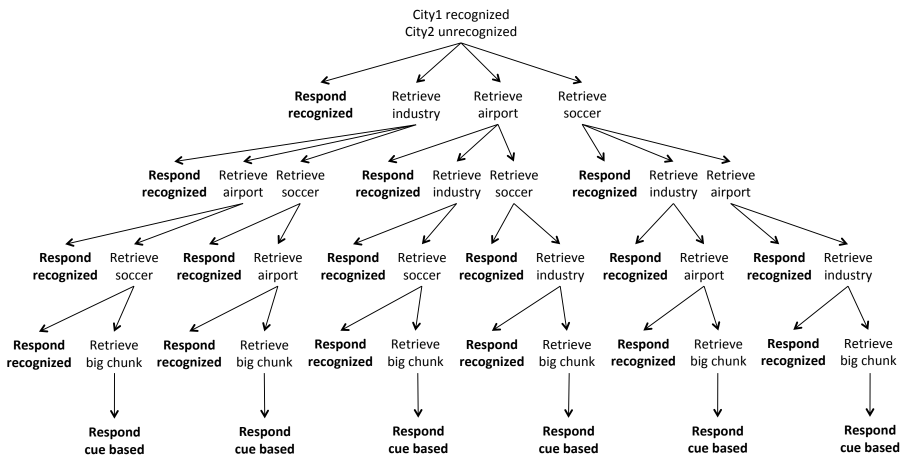

Figure 5.B2 Illustration of the race between different processes in Model 1&4.L.PN. As can be seen, the process to decide with the recognized city races against the retrieval of not-yet-retrieved-cues up to three times. Once all three cues have been retrieved, the process to decide with the recognized city races against the retrieval of intuitive knowledge about the size of the recognized city (the big chunk).

process of Model 1&5.1.PN, in trials where the model is able to retrieve a positive or negative cue value for the first cue. In such trials, the race between different processes is repeated either (a) until the model responds with the recognized city before the decision criterion of $D = 1$ is reached, or (b) until one positive or negative cue has been retrieved and encoded and a decision is made in favor of the recognized city, or (c) until one positive or negative cue has been retrieved and encoded and a decision is made based on the cue (i.e., either in favor of the recognized city or in favor of unrecognized city, depending on

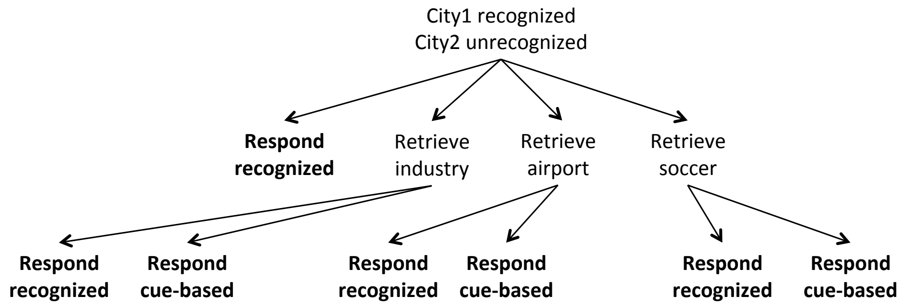

Figure 5.B3 Illustration of the race between different processes in Model 1&5.1.PN, in trials where the first retrieved cue is either positive or negative. As can be seen, in such trials, the process to decide with the recognized city races against the retrieval of the cues once. If a cue is retrieved, the process to decide with the recognized city races against the cue-based response.

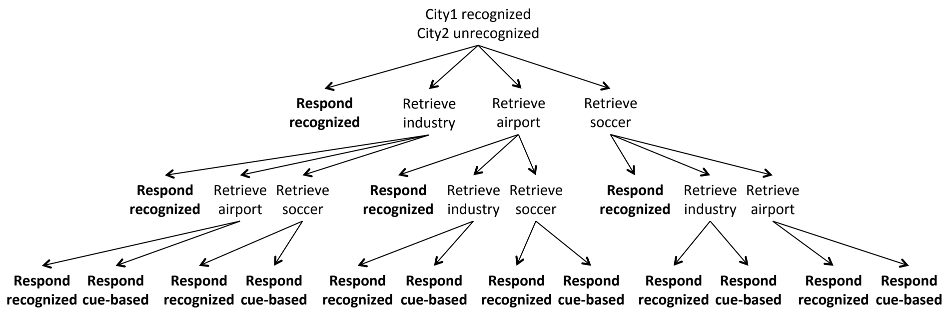

Figure 5.B4 Illustration of the race between different processes in Model 1&5.2.PN, in trials where the first two retrieved cues are either positive or negative. As can be seen, in such trials, the process to decide with the recognized city can race against the retrieval of not-yet-retrieved-cues up to two times. Once two positive or two negative cues have been retrieved, the process to decide with the recognized city races against the cue-based response.

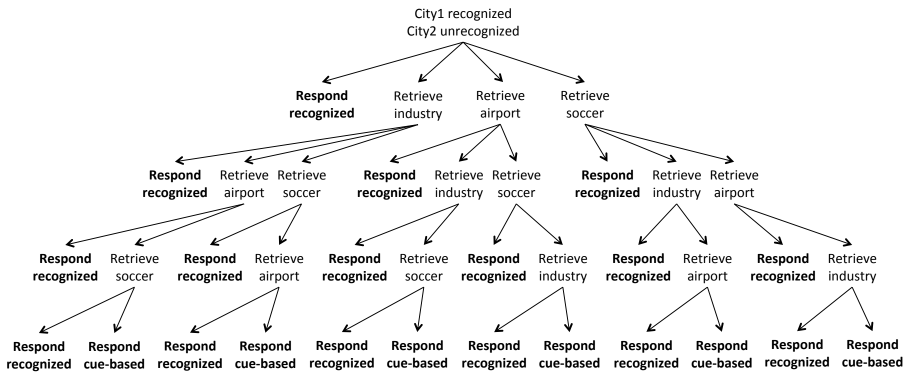

Figure 5.B5 Illustration of the race between different processes in Model 1&5.3.PN, in trials where all three cues of the recognized city are either positive or negative. As can be seen, in such trials, the process to decide with the recognized city can race against the retrieval of not-yet-retrieved-cues up to three times. Once three positive or three negative cues have been retrieved, the process to decide with the recognized city races against the cue-based response.

the retrieved cue). In trials where the value of the first retrieved cue is unknown, the race can continue until one positive or negative cue value has been retrieved. If the decision criterion cannot be reached after all cues were retrieved (i.e., in the 1&5.1 class this will happen if all three cue values are unknown), the model uses recognition as its best guess.

Figure 5.B4 shows the different processes that race against each other at each possible step in the decision process of Model 1&5.2.PN, in trials where the first two retrieved cues are either positive or negative. In such trials, the race is repeated either (a) until the model responds with the recognized city before the decision criterion of $D = 2$ is reached, or (b) until two positive or two negative cue have been retrieved and encoded and a decision is made in favor of the recognized city, or (c) until two positive or two negative cue have been retrieved and encoded and a decision is made based on the cues. In trials where the values of the first two cues are not both positive or negative, the race can continue until all three cues have been retrieved. If the decision criterion cannot be reached after all cues were retrieved, the model uses recognition as its best guess.

Figure 5.B5 shows the different processes that race against each other at each possible step in the decision process of Model 1&5.3.PN, in trials where all three retrieved cues are either positive or negative. In such trials, the race is repeated either (a) until the model responds with the recognized city before the decision criterion of $D = 3$ is reached, or (b) until all three cues are retrieved and encoded and a decision is made in favor of the recognized city, or (c) until all three cues are retrieved and encoded and a decision is made based on the cues. In trials where the values of the three cues are not all positive or negative, the model cannot reach its decision criterion of $D = 3$ cues and will therefore use recognition as its best guess.

Supplementary Material C: Detailed Results for all Models

Fits of All Models – Experiment 1

Visual displays of all models' fits are provided in Figures 5.C1-5.C18. The figures showing the models are arranged in the same order as the models in Tables 5.2-5.5, which describe the models as well as quantify their fit. Each model's fit is plotted for the experimental trials solved by the participants from the recognition group (uneven figure numbers) as well as the trials solved by the cue group (even figure numbers).

In each graph, the upper grey x-axis shows the number of negative cues; the corresponding data points (decisions in Panel A, decision times in Panel B) are plotted in grey font (triangles). In each graph, the lower black x-axis shows the number of positive cues; the corresponding data points are plotted in black font (circles).

Recognition group

As is to be expected, in the recognition group, those models that always choose recognized cities (see Table 5.3) fit the human decisions perfectly (RMSD of 0 in Table 5.4). Specifically, the Model 1, 2, 3 and 1&3 classes (Figures 5.C1, 5.C3) always decide in favor of recognized cities, because recognition is the only decision rule these models implement.

Also Models 5.1.P, 5.2.P, and 5.3.P (Figure 5.C11), 1&5.1.P, 1&5.1.P.F (Figure 5.C13), 1&5.2.P, 1&5.2.P.F (Figure 5.C15), and 1&5.3.P, 1&5.3.P.F (Figure 5.C17), always choose recognized cities. However, these models base such decisions on positive cues in addition to recognition. These models cannot choose unrecognized cities, because they cannot retrieve negative cues.

Finally, although models 5.3.PN (Figure 5.C11), 1&5.3.PN, and 1&5.3.PN.F (Figure 5.C17) do have access to negative cues, they always choose recognized cities, because the models require at least three negative cues (*D* = 3) to decide against recognized cities and in Experiment 1 participants were only taught up to two negative cues (Table 5.1). None of the simple models that fit the human decisions of the recognition group (Model classes 1, 2, 3, and Models 5.1.P, 5.2.P, 5.3.P, and 5.3.PN) are able to fit the human decision times. Model 1 does not retrieve cues and therefore the cues do not affect timing (Figure 5.C1). The Model 2 and 3 classes and those representatives of the Model 5 class that always chose the recognized city are able to more closely approximate the human decision times, as they show the tendency to produce slower decision times as a function of increasing amounts of negative cues (Figures 5.C1 and 5.C11); however, these model classes fail to fit the spread of the decision time distributions, resulting in high RMSDs (Table 5.4).

The race models that fit the human decisions of the recognition group (the Model 1&3 class, Figure 5.C3; and Models 1&5.1.P, 1&5.1.P.F, Figure 5.C13; 1&5.2.P, 1&5.2.P.F, Figure 5.C15; 1&5.3.P, 1&5.3.P.F, 1&5.3.PN, 1&5.3.PN.F, Figure 5.C17) differ with respect to their decision time fit. Whereas they all show the tendency to produce slower decision times with an increasing amount of negative cues (as found in the human data), the Model 1&3 and 1&5.3 classes, as well as the P versions of the 1&5.2 class produce a decision time distribution that is closest to the human data, because these models predict the largest spread in the decision times.

Cue group

Human decisions in favor of recognized cities tend to increase as a function of the number of positive cues and decrease as a function of the number of negative cues (e.g., Figure 5.C2). As is to be expected, the models described in the previous section (i.e., see recognition group) do not fit this effect, because these models only produce decisions in favor of recognized cities (Figures 5.C2, 5.C4, 5.C12, 5.C14, 5.C16, 5.C18).

In contrast, models that use cue knowledge implicitly in the decision, the Model 4 and 1&4 classes, fit the pattern of decisions. In these models, the tendency to decide for the unrecognized city increases with the number of negative cues (Figures 5.C6, 5.C8, 5.C10). The models differ with respect to the overall proportion of choices for the recognized city. For example, Model 4.H.PN fits the overall proportion well, whereas Model 4.L.PN underestimates the proportion of choices for the recognized city.

Model 5.1.PN, 5.2.PN, 1&5.1.PN, 1&5.2.PN, 1&5.1.PN.F, and 1&5.2.PN.F all of which use positive and negative cue knowledge explicitly in the decision and are able to reach their decision criterion of D negative cues to decide against the recognized city in this experiment, exhibit a tendency to choose unrecognized cities as a function of the number of negative cues. However, these models predict a drop in decisions for the recognized city once the decision criterion D is reached, which was not found in the human data (Figures 5.C12, 5.C14, 5.C16).

None of the simple models that sometimes decide against the recognized city are able to predict the human decision time distribution (Figures 5.C6, 5.C12). The race models differ in their ability to predict the decision times (Figures 5.C8, 5.C10, 5.C14, 5.C16), with none of the models fitting the combination of decisions and decision times as well as the winning Model 1&4.L class.

All Models' Generalizability – Experiment 2

Visual displays of all models' fits for Experiment 2 are provided in Figures 5.C19-5.C36. As for Experiment 1, the models are presented in the same order as in Tables 5.2-5.5, and each model's prediction is shown separately for the recognition group (uneven figure numbers) and the cue group (even figure numbers).

Recognition group

As is to be expected, in the recognition group, the same model classes as in Experiment 1 accurately predict the human decisions (*simple models*: Model 1, 2, 3, class, Figure 5.C19; and the P versions of the Model 5 class, Figure 5.C29; *race models*: Model 1&3 class, Figure 5.C21; and the P versions of the Model 1&5 class, Figures 5.C31, 5.C33, 5.C35). As explained in the main text, exceptions are Models 5.3.PN, 1&5.3.PN, and 1&5.3.PN.F

(Figures 5.C29, 5.C35), which always chose the recognized city in Experiment 1, but which can decide against recognized cities in Experiment 2.

As in Experiment 1, none of the simple models that accurately predict the human decisions is able to additionally predict the decision time distribution (Figures 5.C19, 5.C29). The race models differ in their ability to predict the decision times (Figures 5.C21, 5.C31, 5.C33, 5.C35). As in Experiment 1, the Model 1&3 class as well as the P versions of the Model 1&5.2 and 1&5.3 classes produce a decision time distribution that most closely resembles the human data, because these models predict a large spread in the decision times.

Cue group

In contrast to Experiment 1, in the cue group, the human decisions exhibit a drop in the proportion of decisions for the recognized city when three negative cues (or zero positive cues) are associated with the recognized city. Predicting a gradual decrease of decisions with an increasing number of negative cues, models that use cues implicitly (Model 4 and 1&4 classes; Figures 5.C24, 5.C26, 5.C28) have difficulties to predict this new pattern in Experiment 2. As can be seen, these models only capture the gradual decrease in decisions from zero to one negative cues, but not the drop that is observed for decisions with three negative cues.

Models that use positive and negative cue knowledge explicitly (the PN versions of the Model 5 and 1&5 classes) do predict a drop in the proportion of decisions for the recognized city once their decision criterion D negative cues is reached. This drop is overestimated by the simple models (PN versions of Model 5 class, Figure 5.C30) and by the race Models 1&5.1.PN and 1&5.1.PN.F (Figure 5.C32). Using a decision criterion of $D = 2$ and $D = 3$ cues, respectively, Models 1&5.2.PN, 1&5.2.PN.F (Figure 5.C34), 1&5.3.PN, and 1&5.3.PN.F (Figure 5.C36) capture the drop in human decisions.

As in Experiment 1, none of the simple models that sometimes decide against the recognized city is able to predict the human decision time distribution (Figures 5.C24, 5.C30). The race models differ in their ability to predict the decision times (Figures 5.C26, 5.C28, 5.C32, 5.C34, 5.C36), with the models that predict the largest spread in the decision times fitting the human decision time distribution best (Model 1&4 class and Models 1&5.3.PN; 1&5.3.PN.F).

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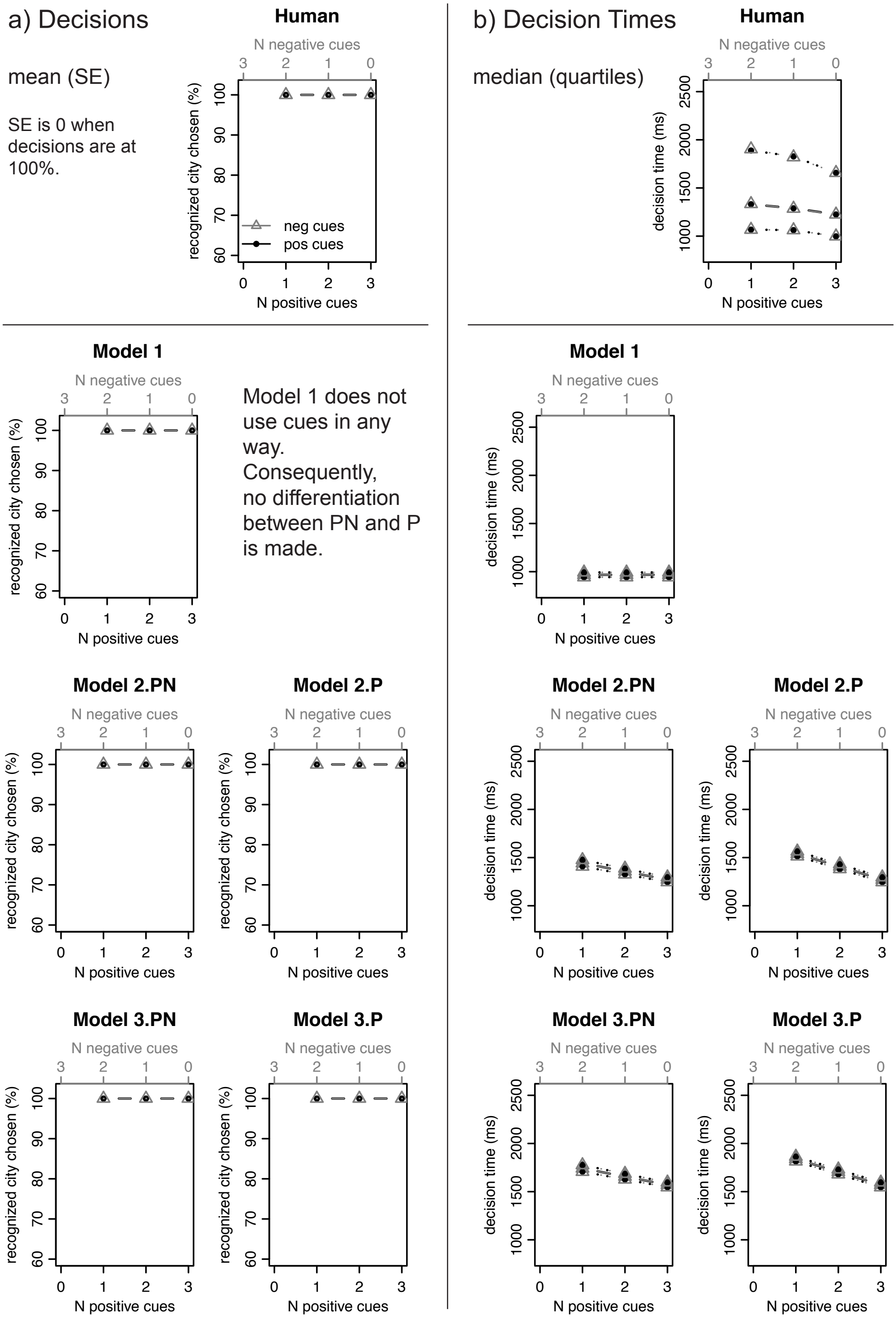


Figure 5.C1 Model 1, 2, and 3 classes and human data—recognition group—Experiment 1.

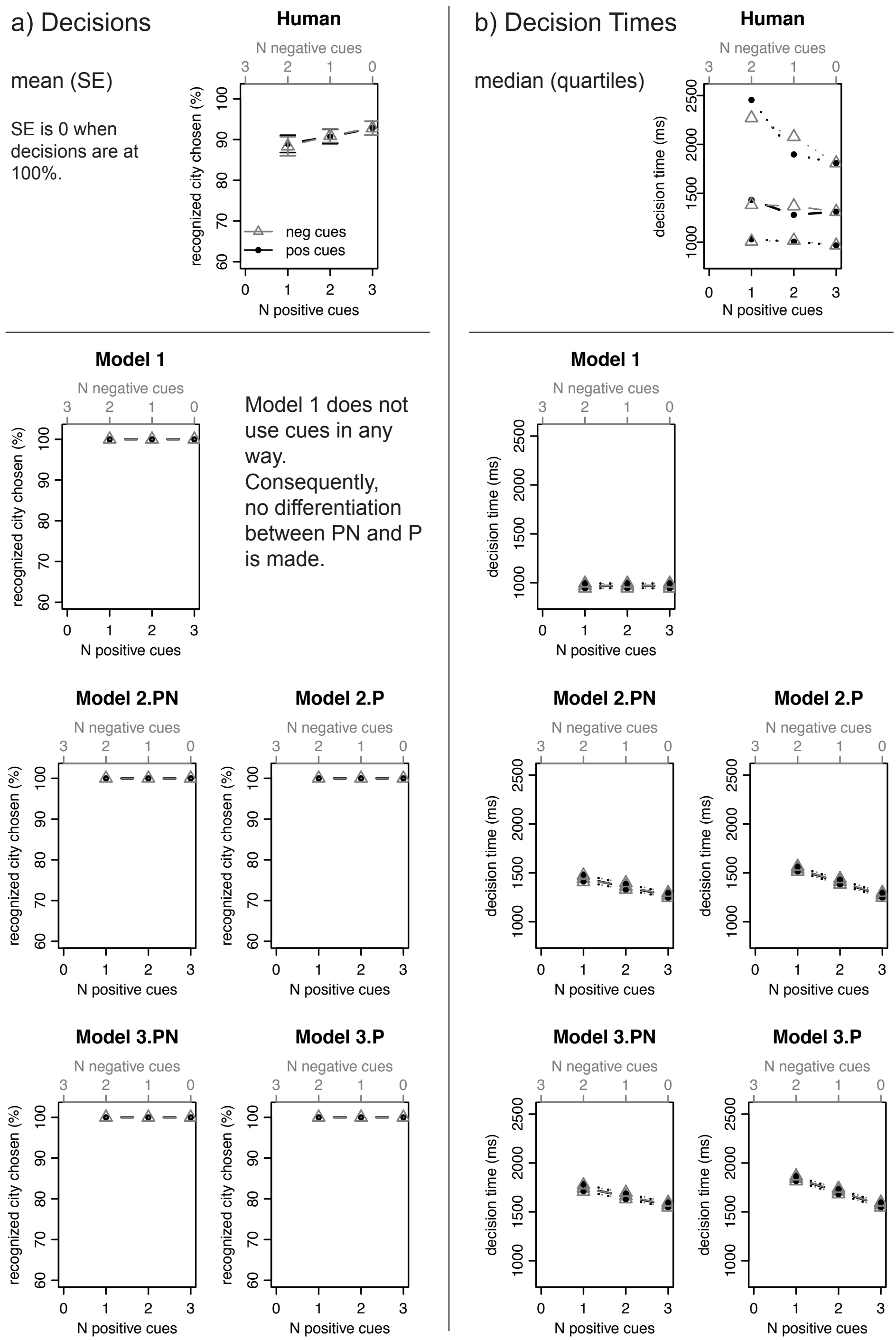


Figure 5.C2 Model 1, 2, and 3 classes and human data—cue group—Experiment 1.

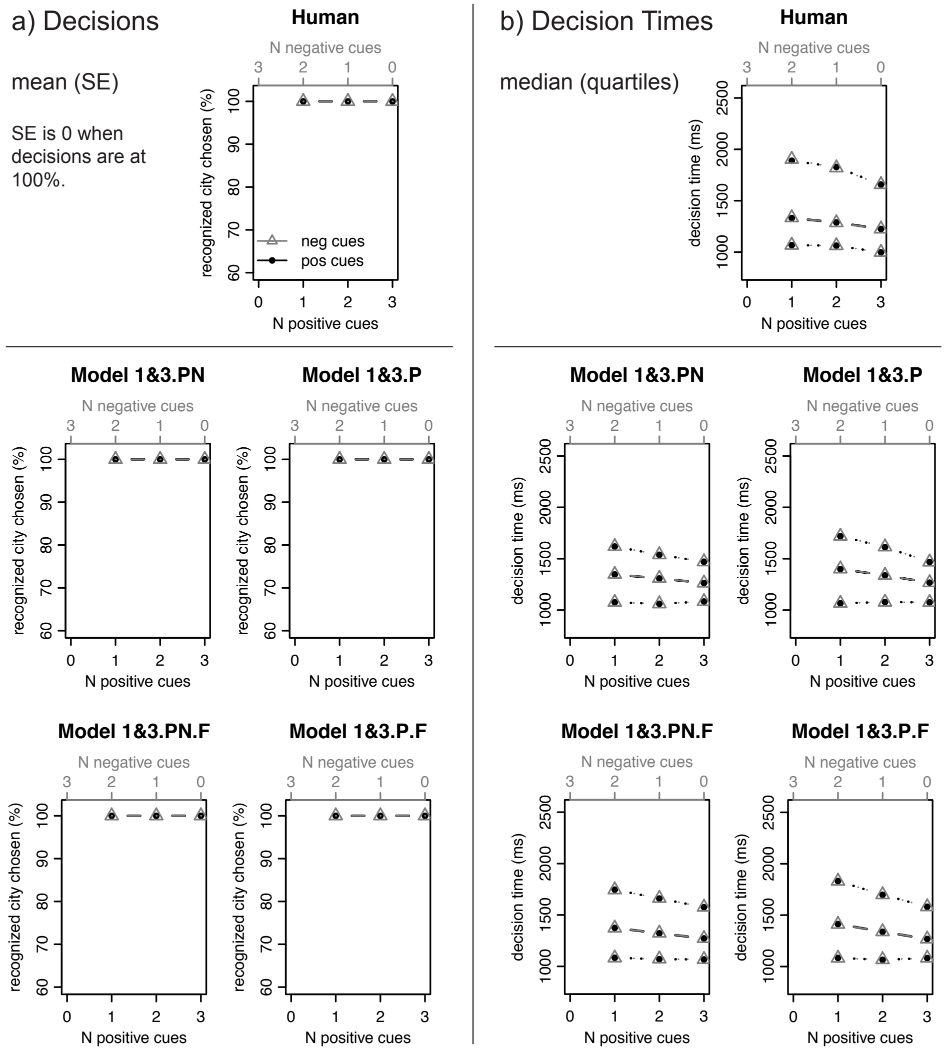


Figure 5.C3 Model 1&3 class and human data—recognition group—Experiment 1.

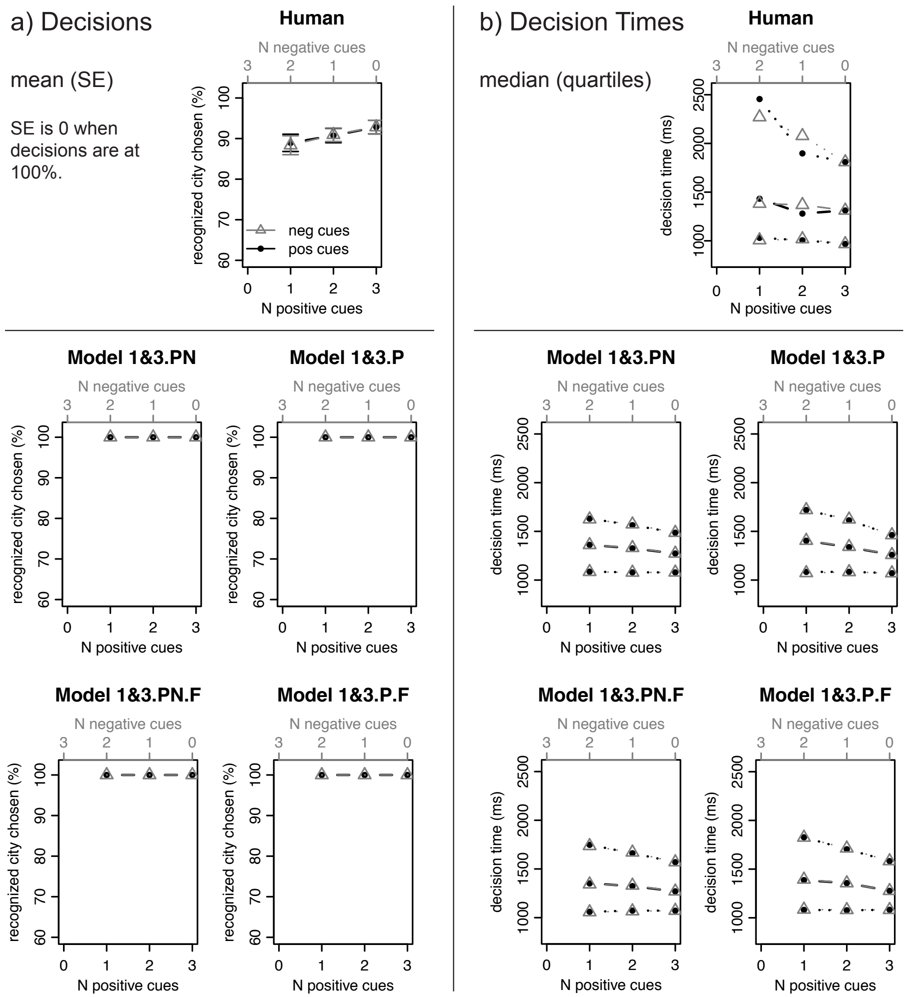


Figure 5.C4 Model 1&3 class and human data—cue group—Experiment 1.

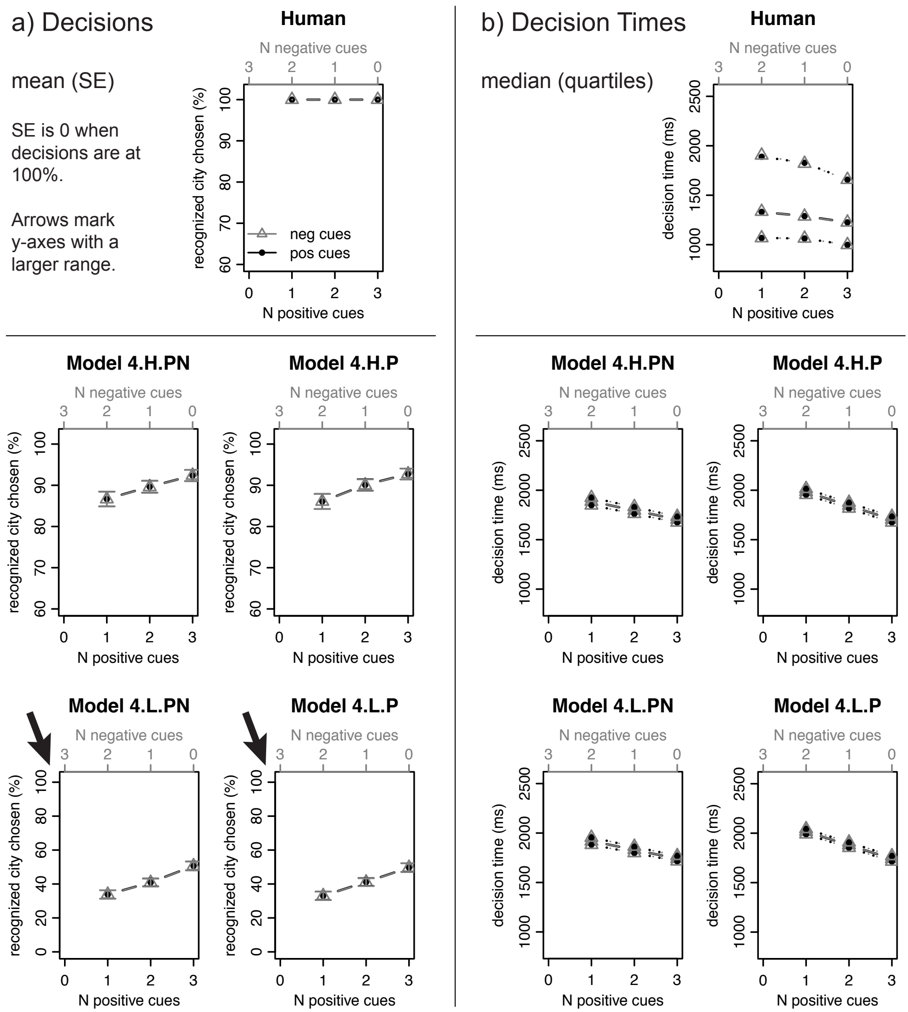


Figure 5.C5 Model 4 class and human data—recognition group – Experiment 1.

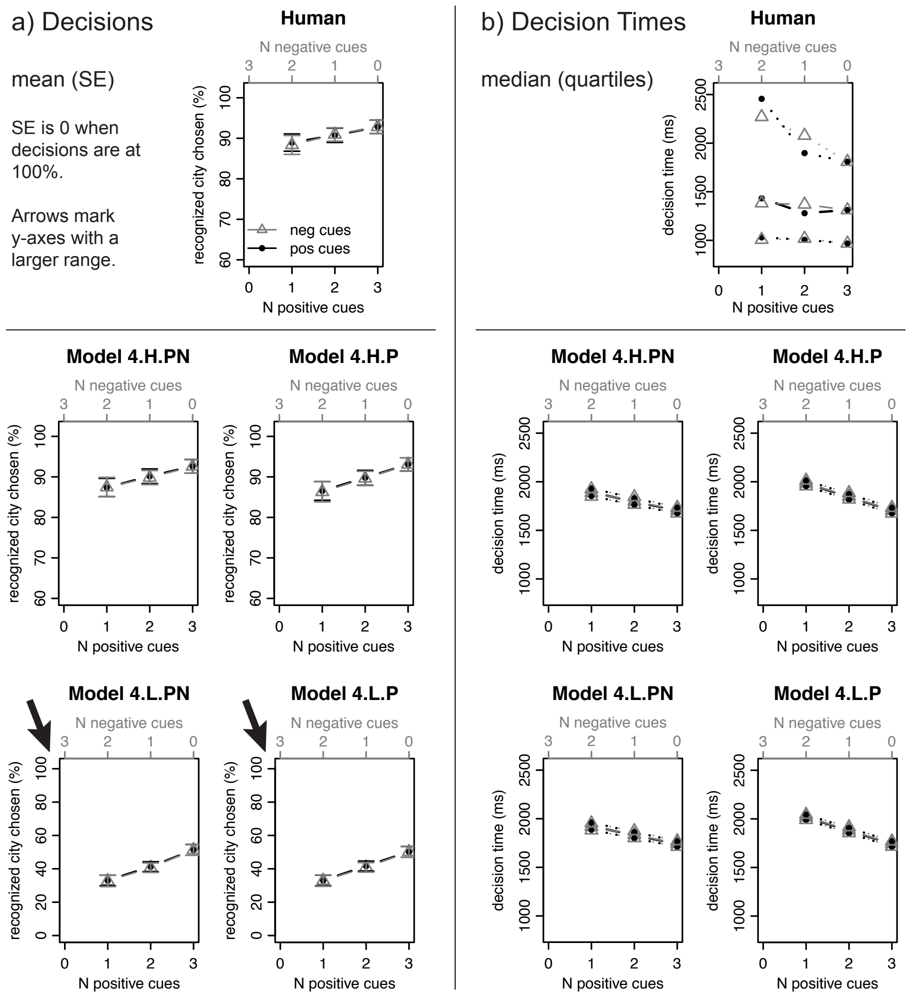


Figure 5.C6 Model 4 class and human data—cue group—Experiment 1.

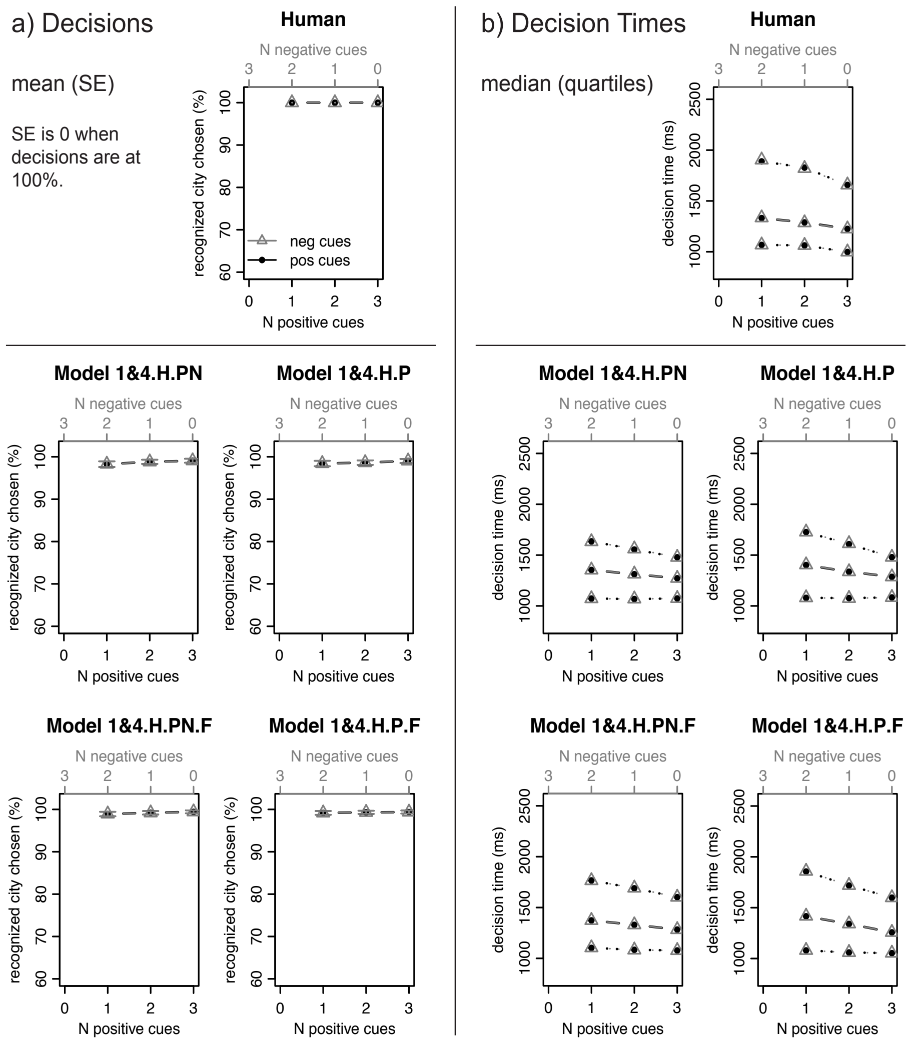


Figure 5.C7 Model 1&4.H class and human data—recognition group—Experiment 1.

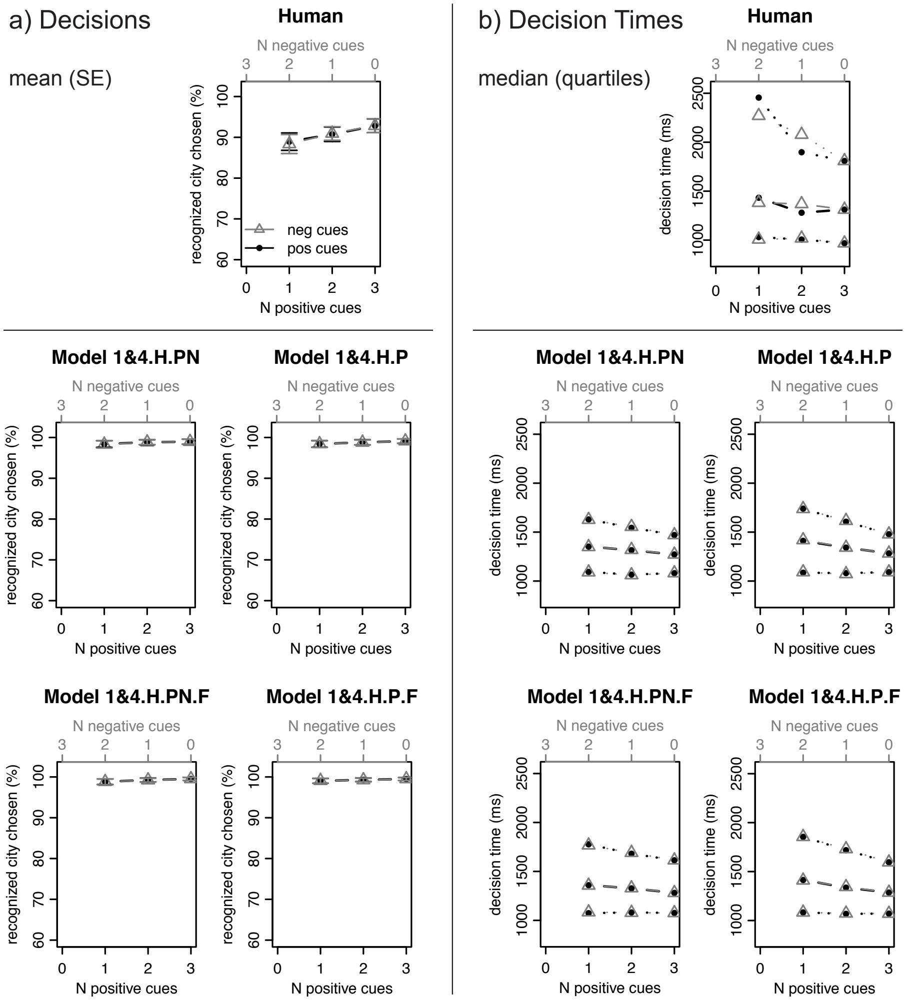


Figure 5.C8 Model 1&4.H class and human data—cue group—Experiment 1.

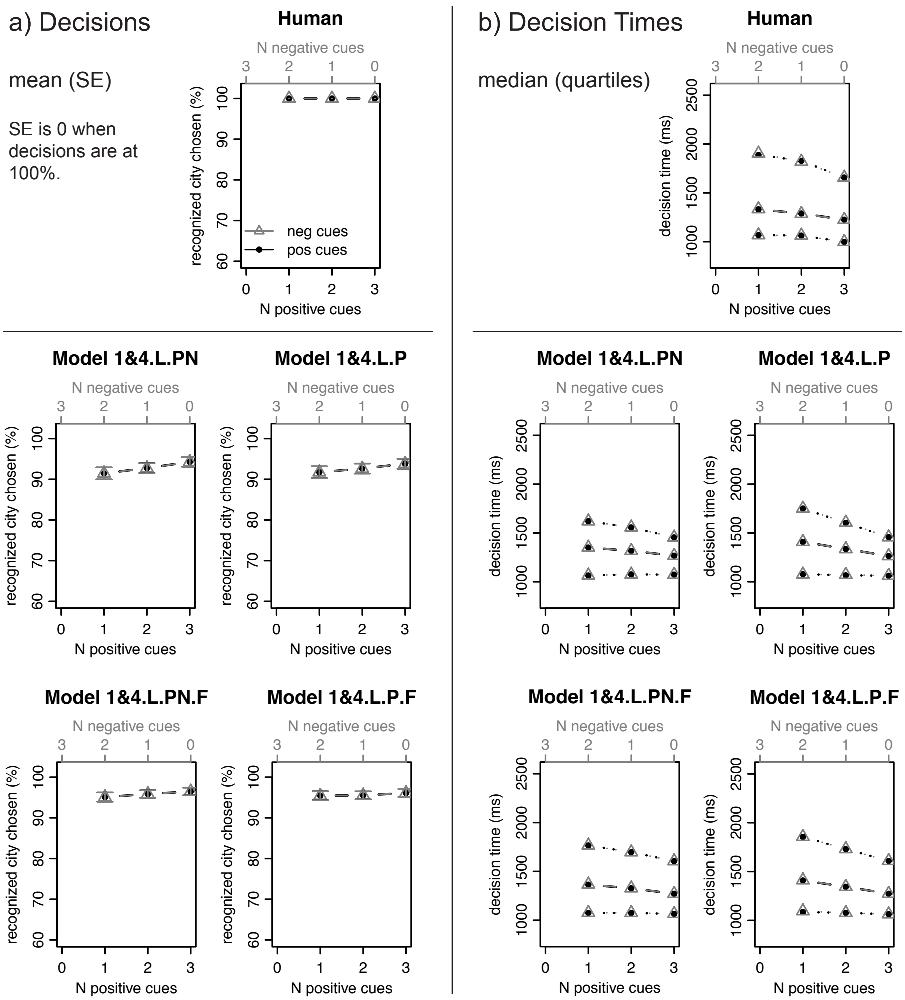


Figure 5.C9 Model 1&4.L class and human data—recognition group—Experiment 1.

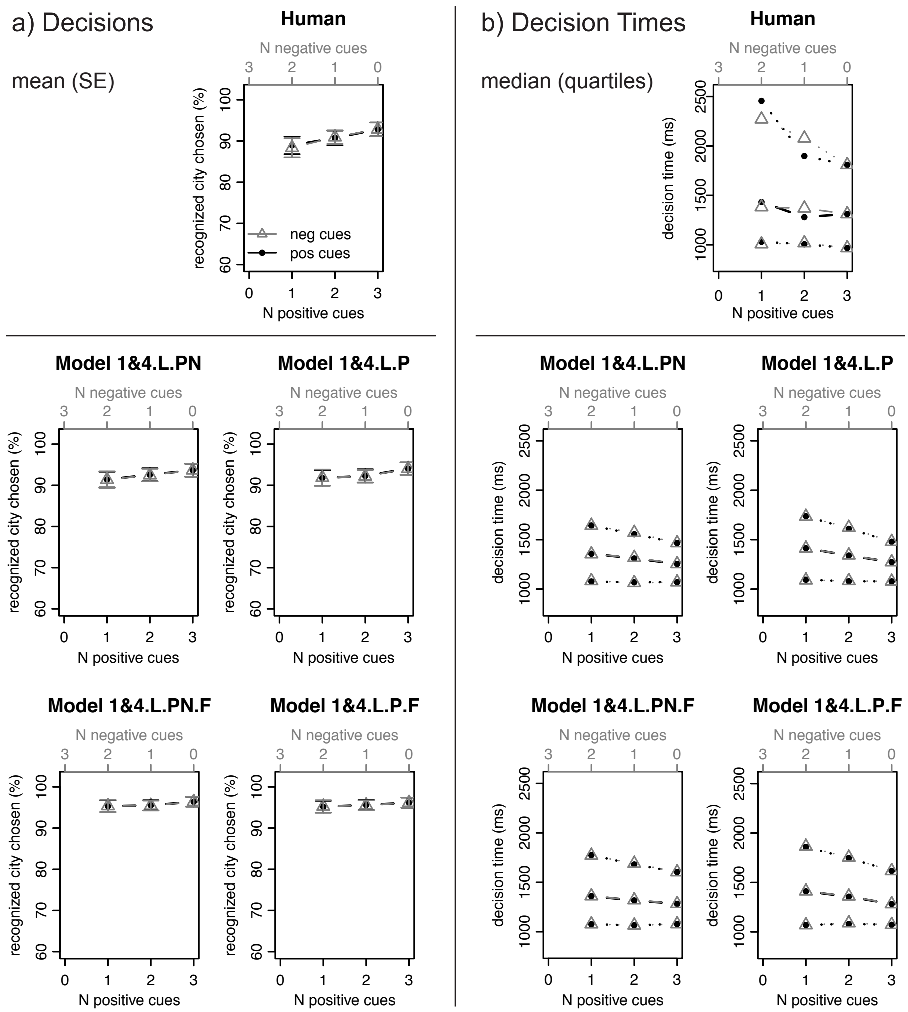


Figure 5.C10 Model 1&4.L class and human data—cue group—Experiment 1.

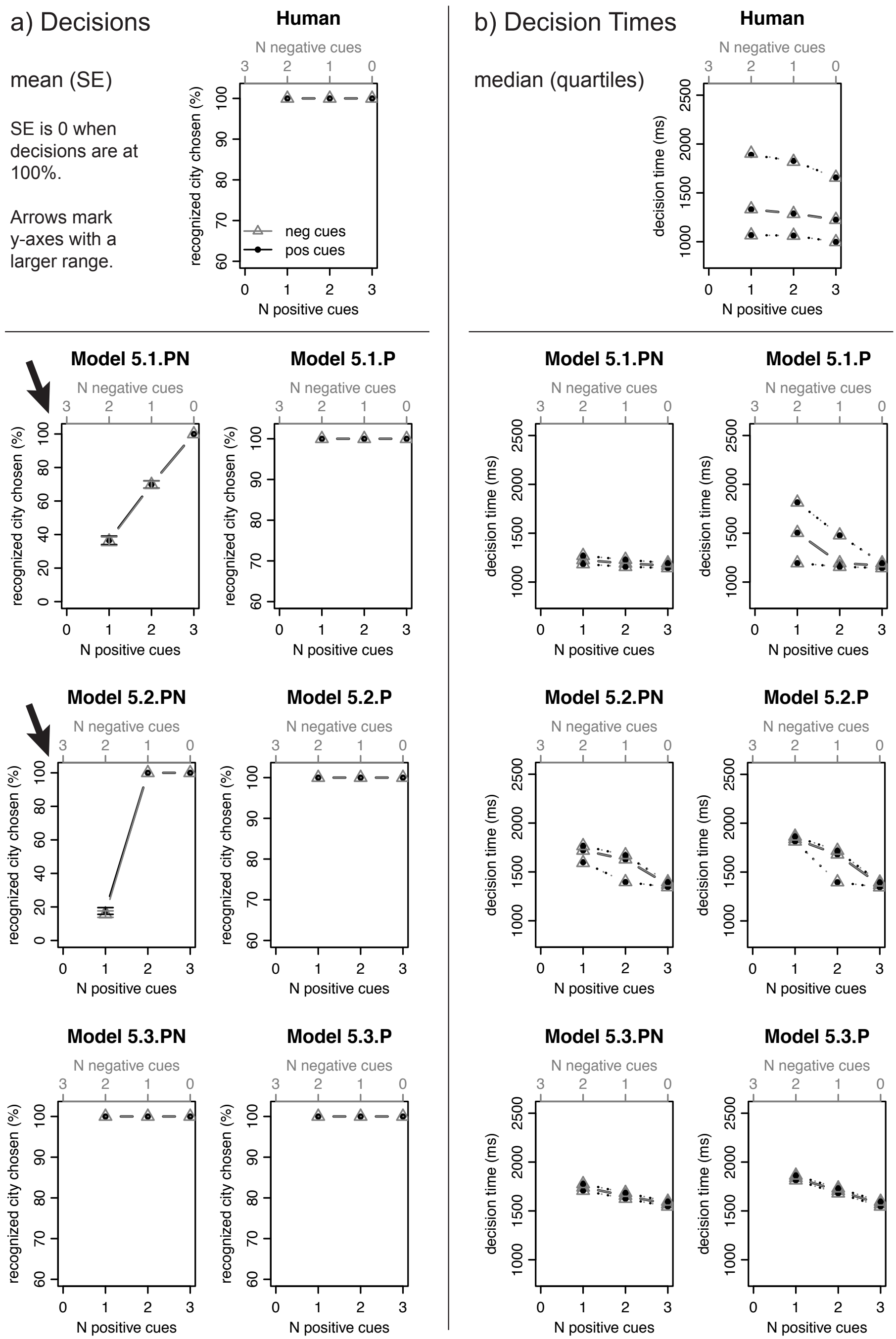


Figure 5.C11 Model 5 class and human data—recognition group – Experiment 1.

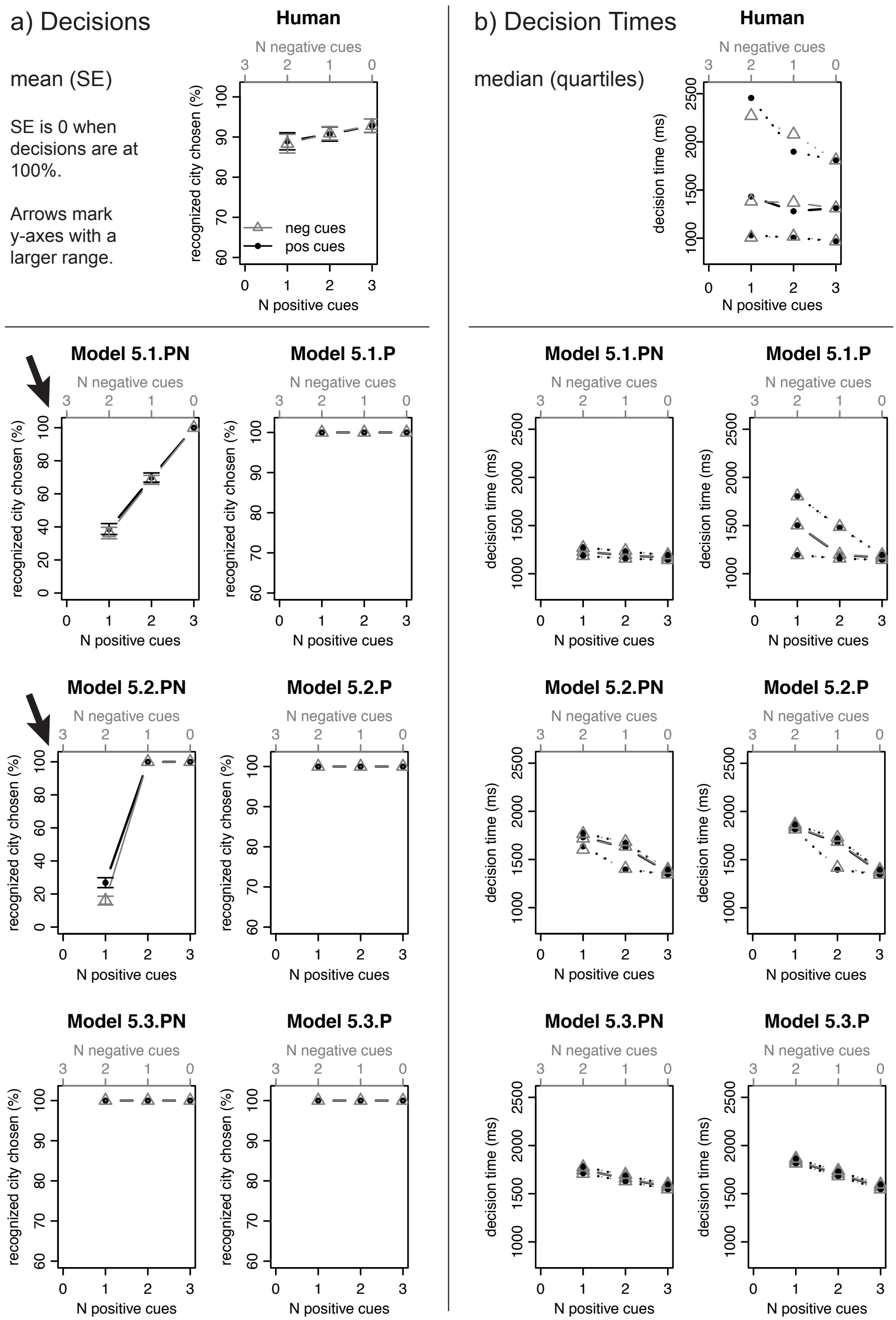


Figure 5.C12 Model 5 class and human data—cue group—Experiment 1.

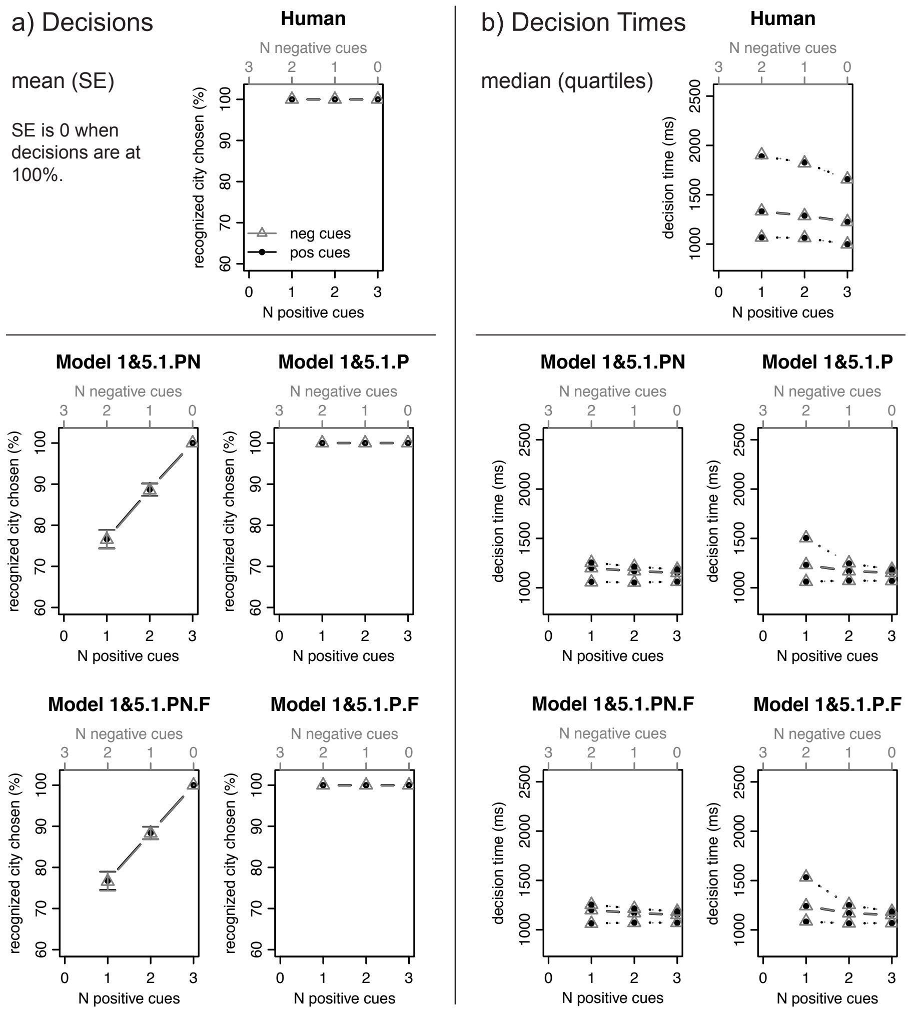


Figure 5.C13 Model 1&5.1 class and human data—recognition group—Experiment 1.

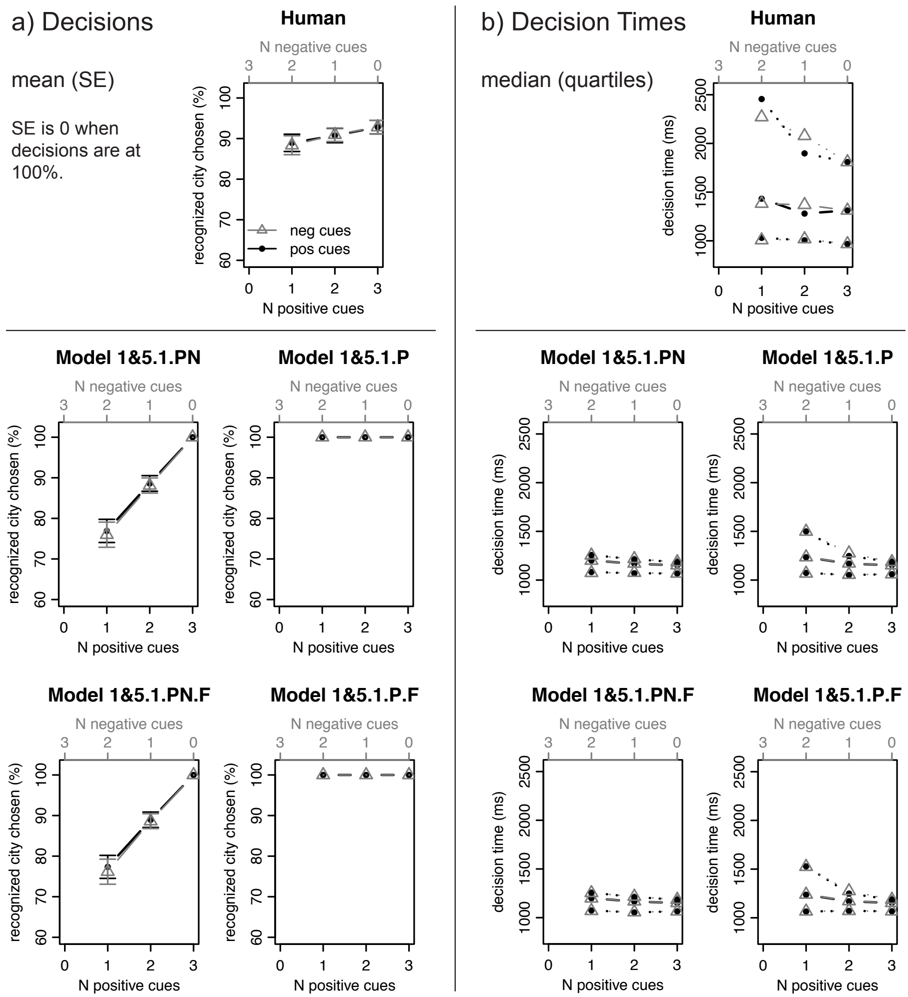


Figure 5.C14 Model 1&5.1 class and human data—cue group—Experiment 1.

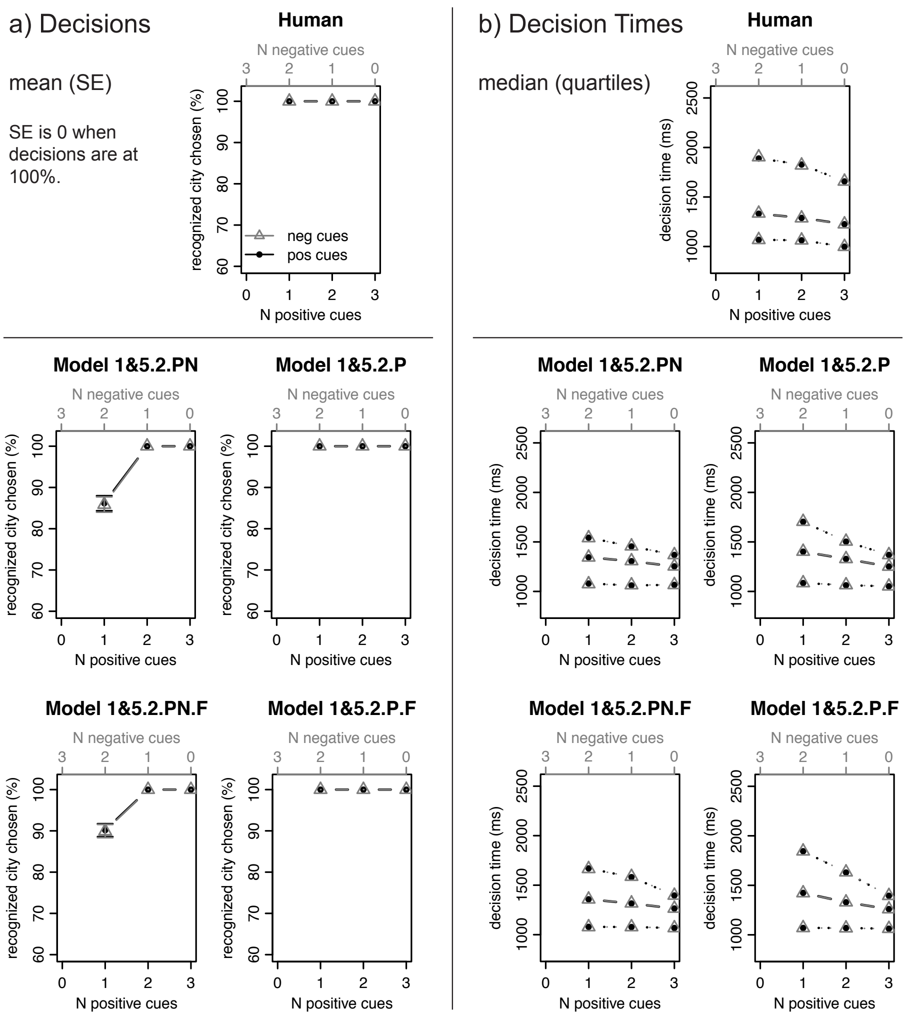


Figure 5.C15 Model 1&5.2 class and human data—recognition group—Experiment 1.

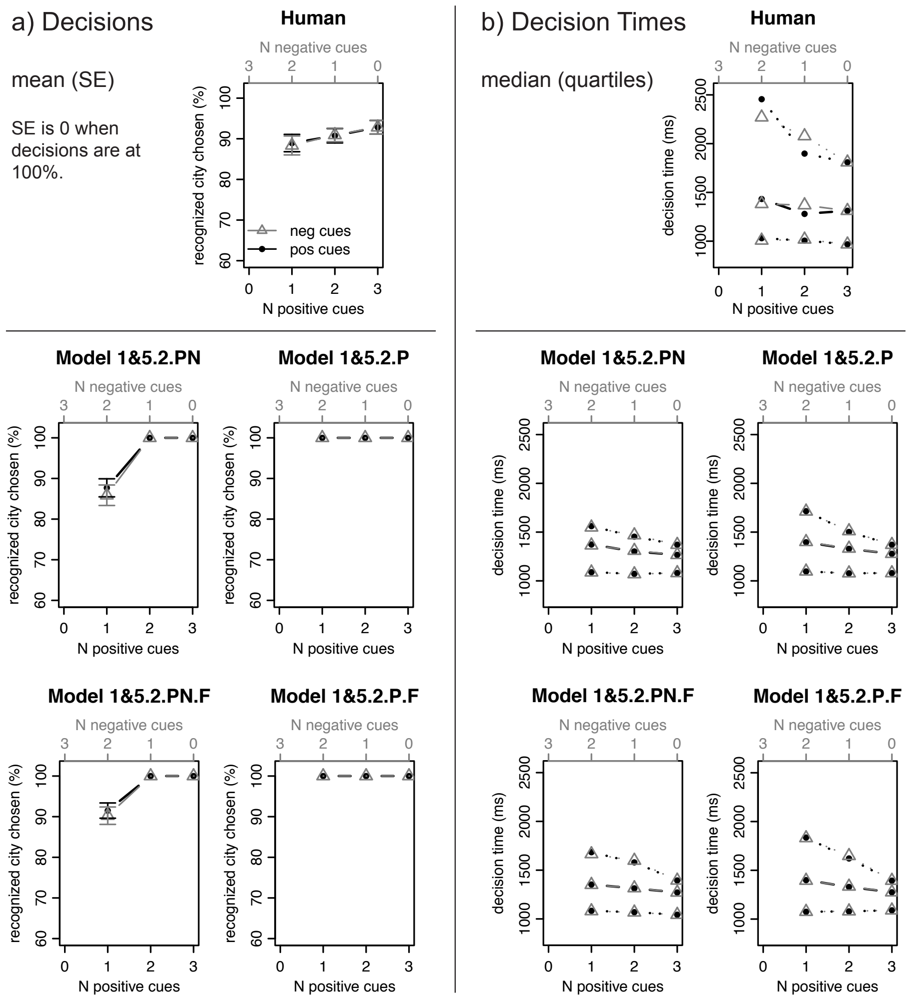


Figure 5.C16 Model 1&5.2 class and human data—cue group—Experiment 1.

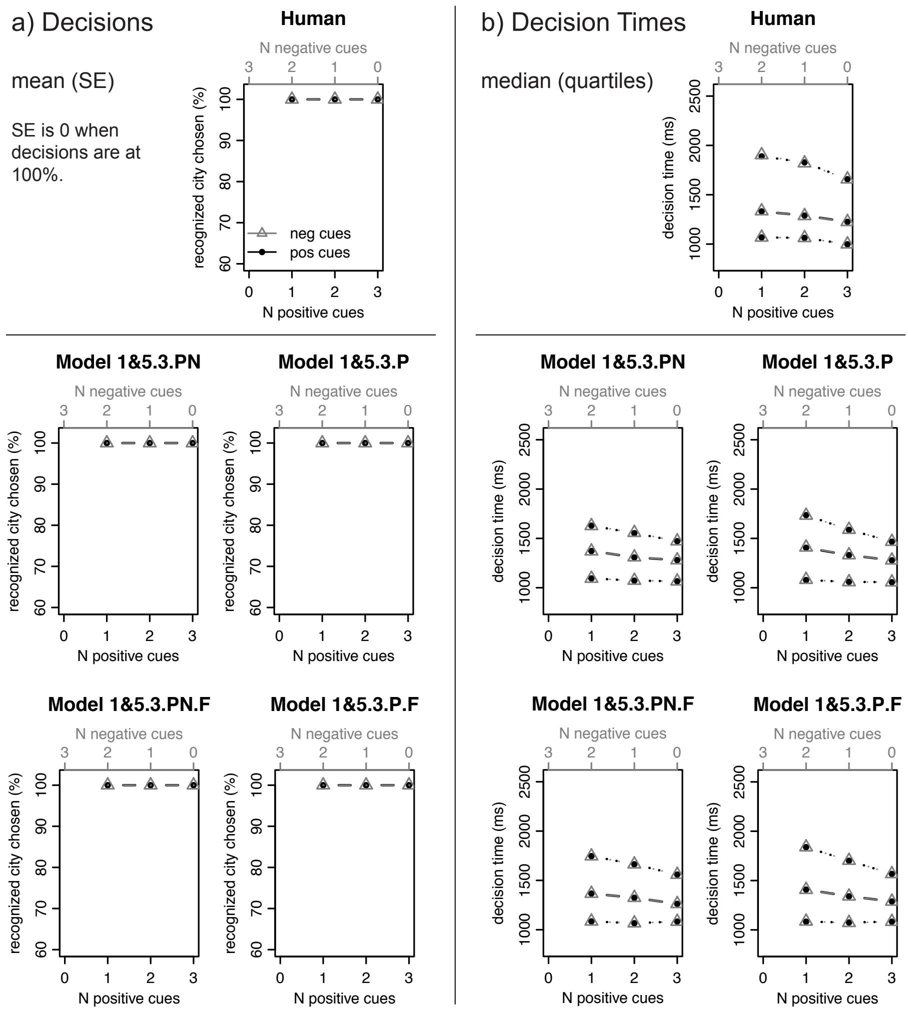


Figure 5.C17 Model 1&5.3 class and human data—recognition group—Experiment 1.

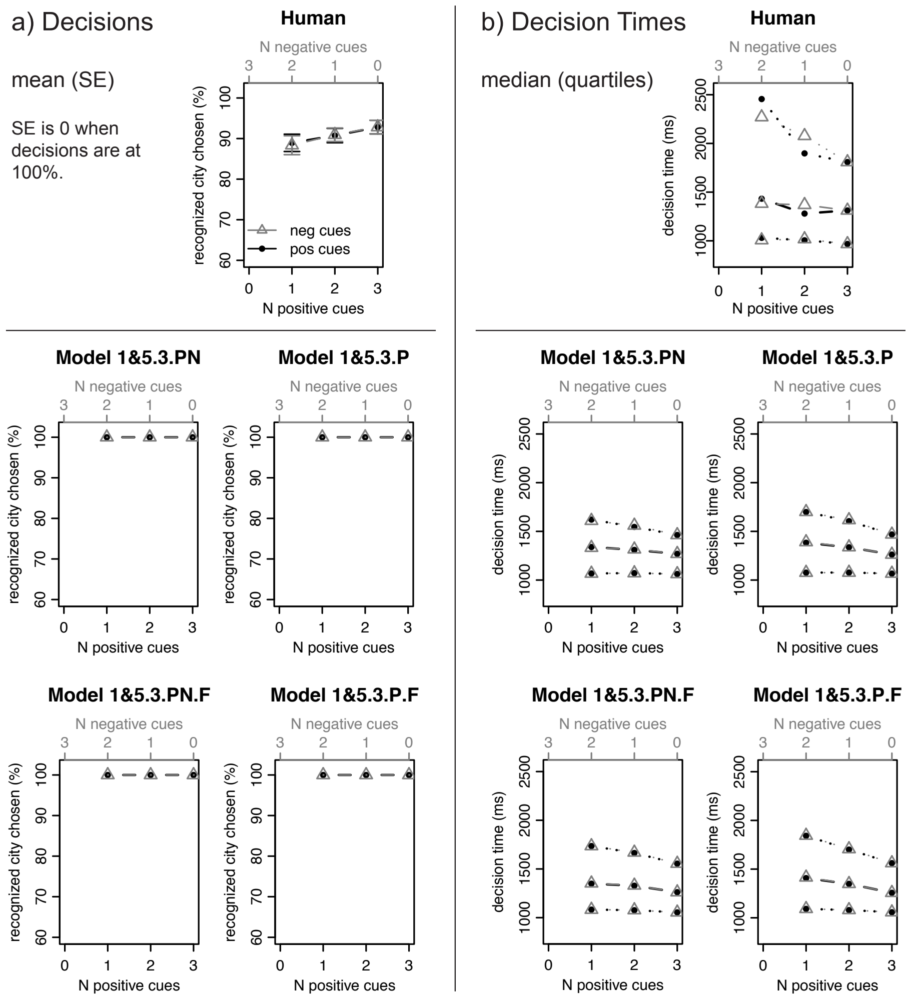


Figure 5.C18 Model 1&5.3 class and human data—cue group—Experiment 1.

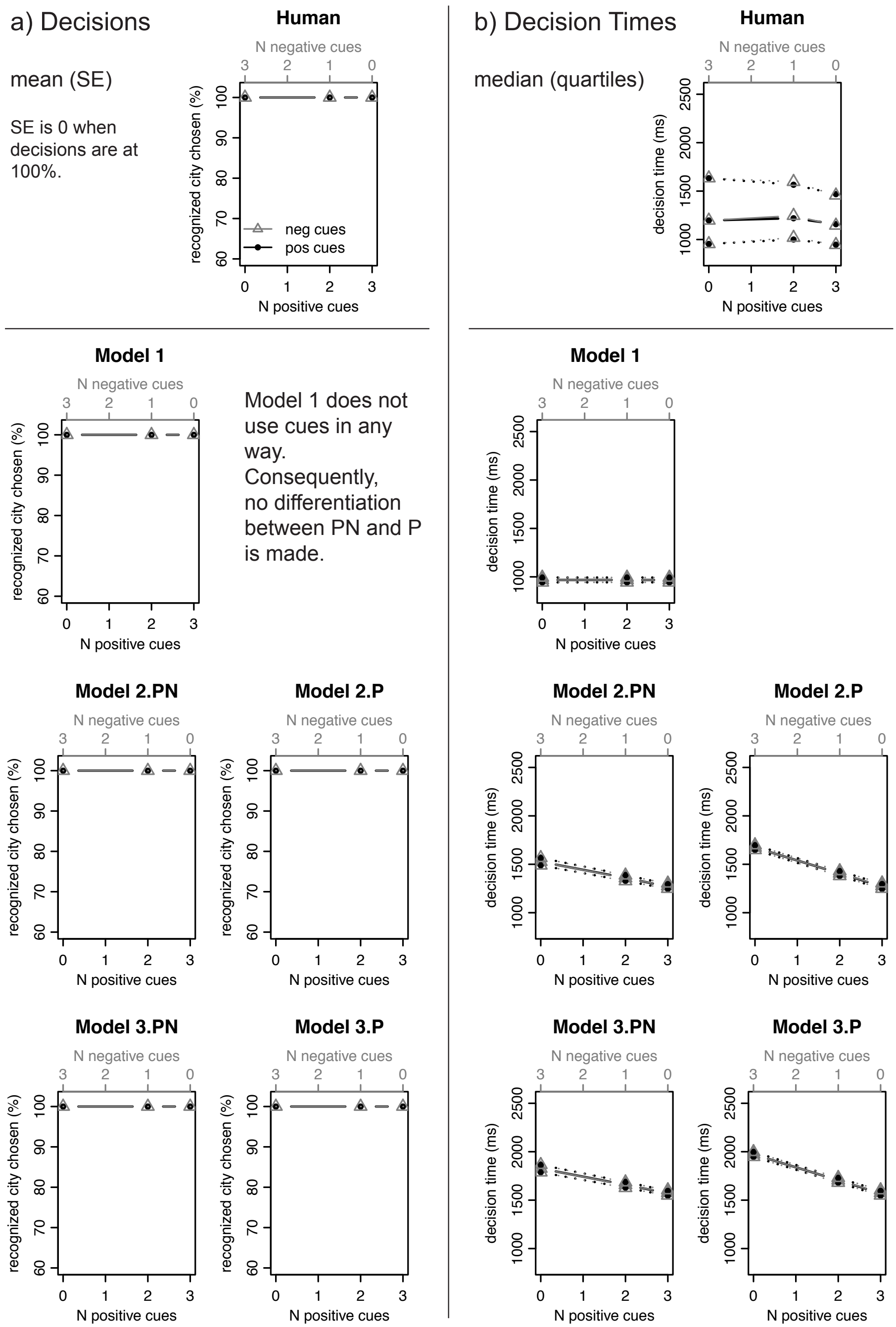


Figure 5.C19 Model 1, 2, and 3 classes and human data—recognition group—Experiment 2.

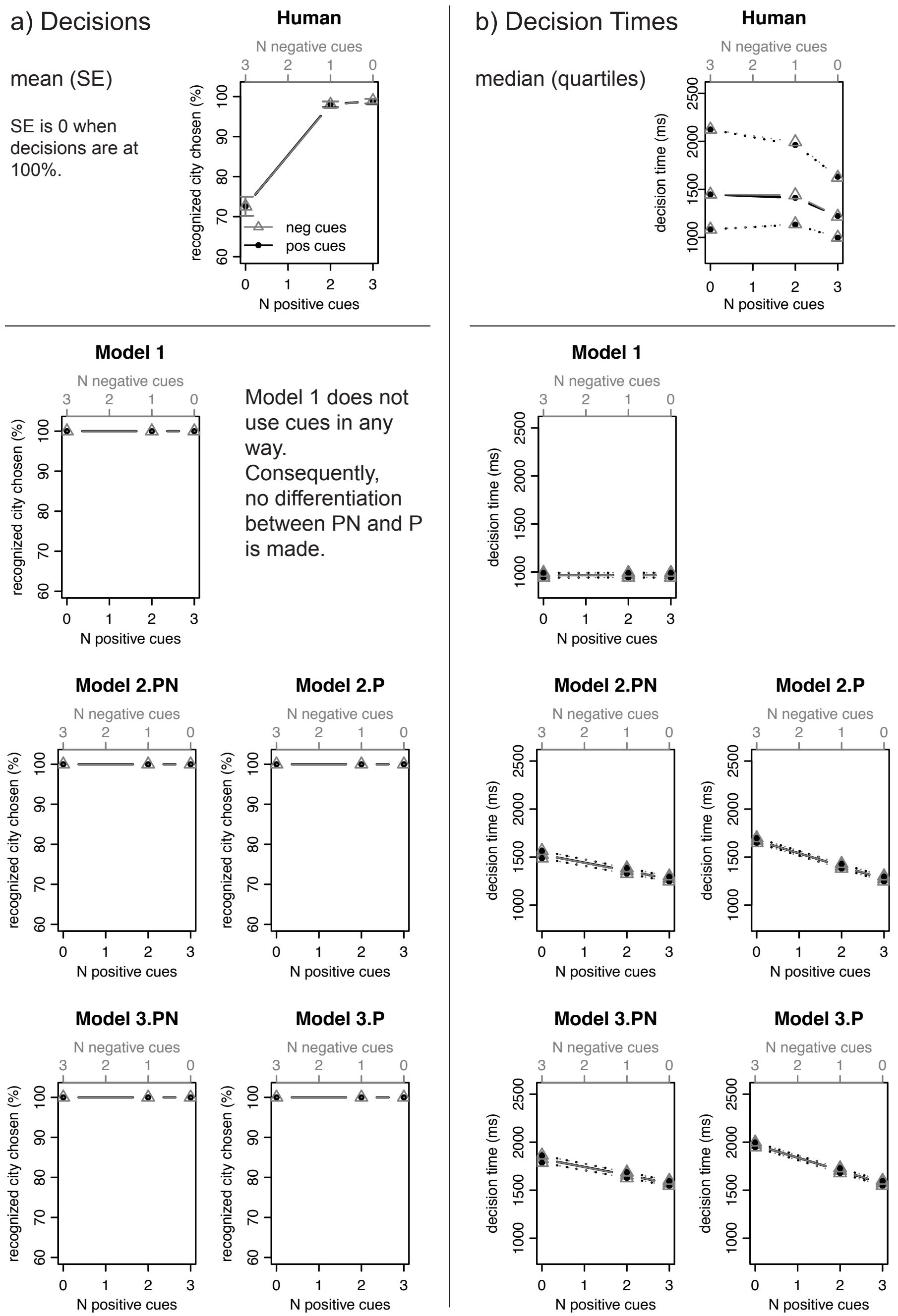


Figure 5.C20 Model 1, 2, and 3 classes and human data—cue group—Experiment 2.

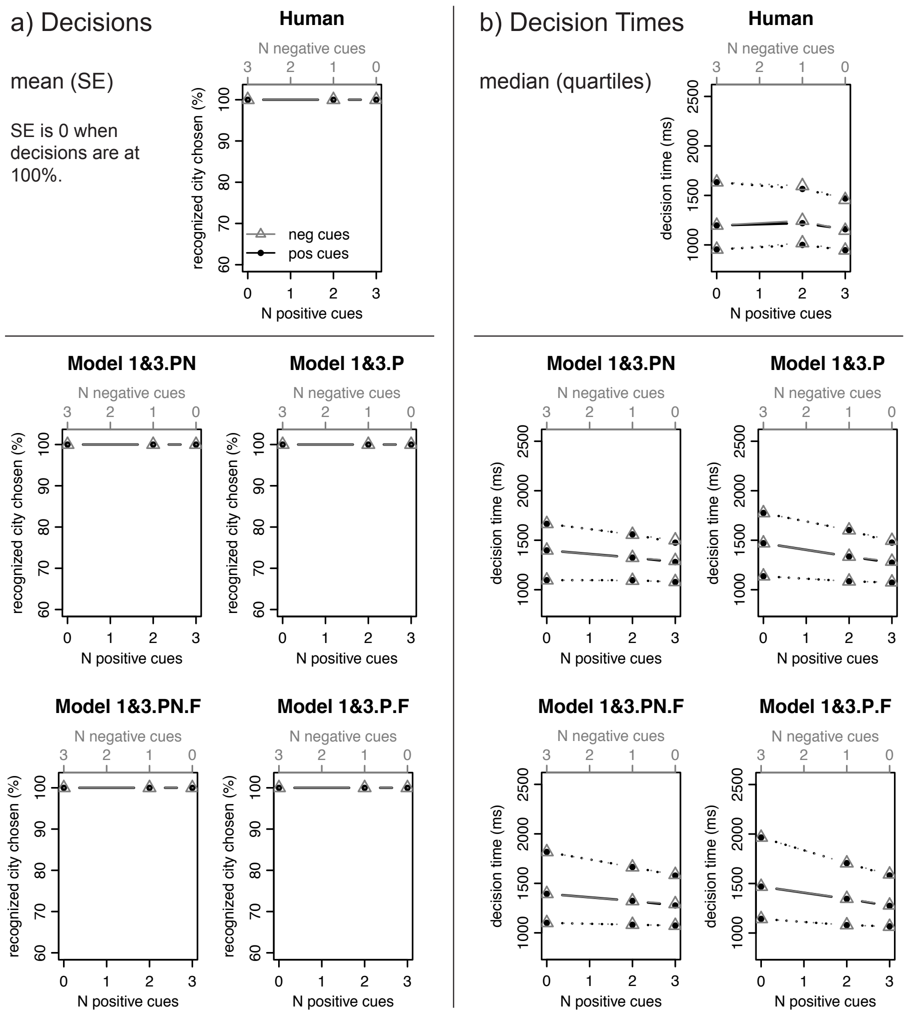


Figure 5.C21 Model 1&3 class and human data—recognition group—Experiment 2.

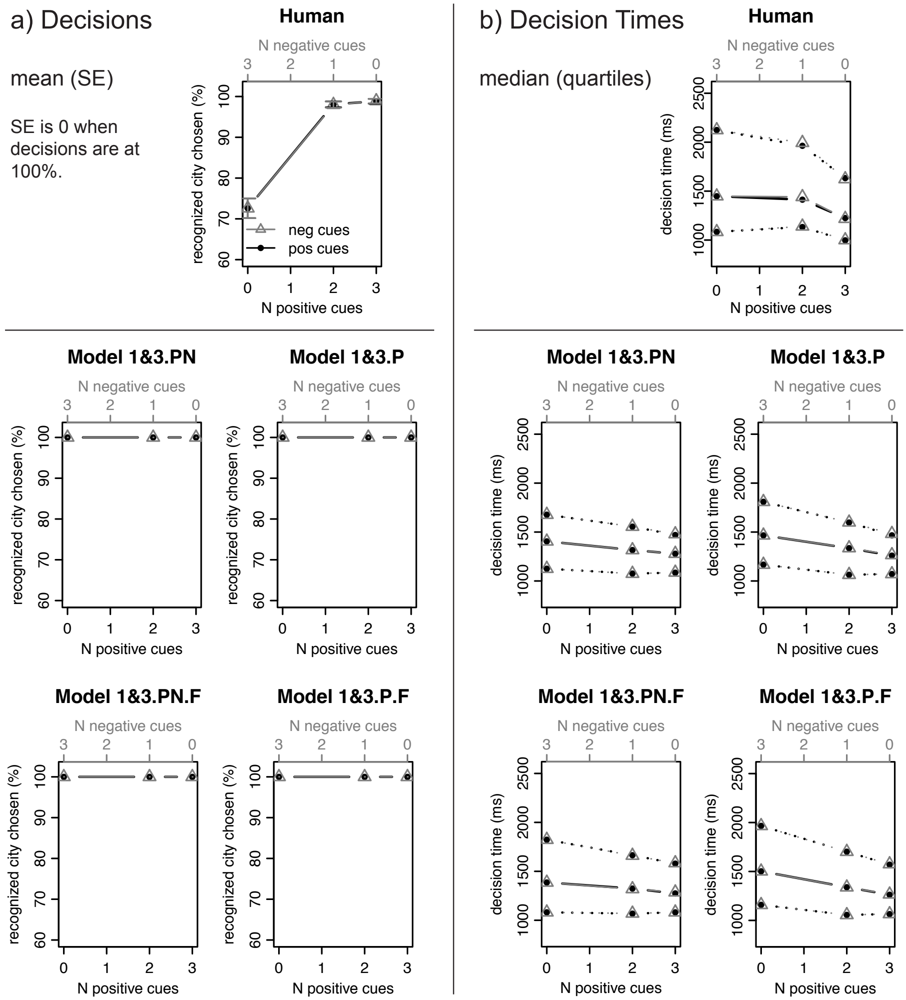


Figure 5.C22 Model 1&3 class and human data—cue group—Experiment 2.

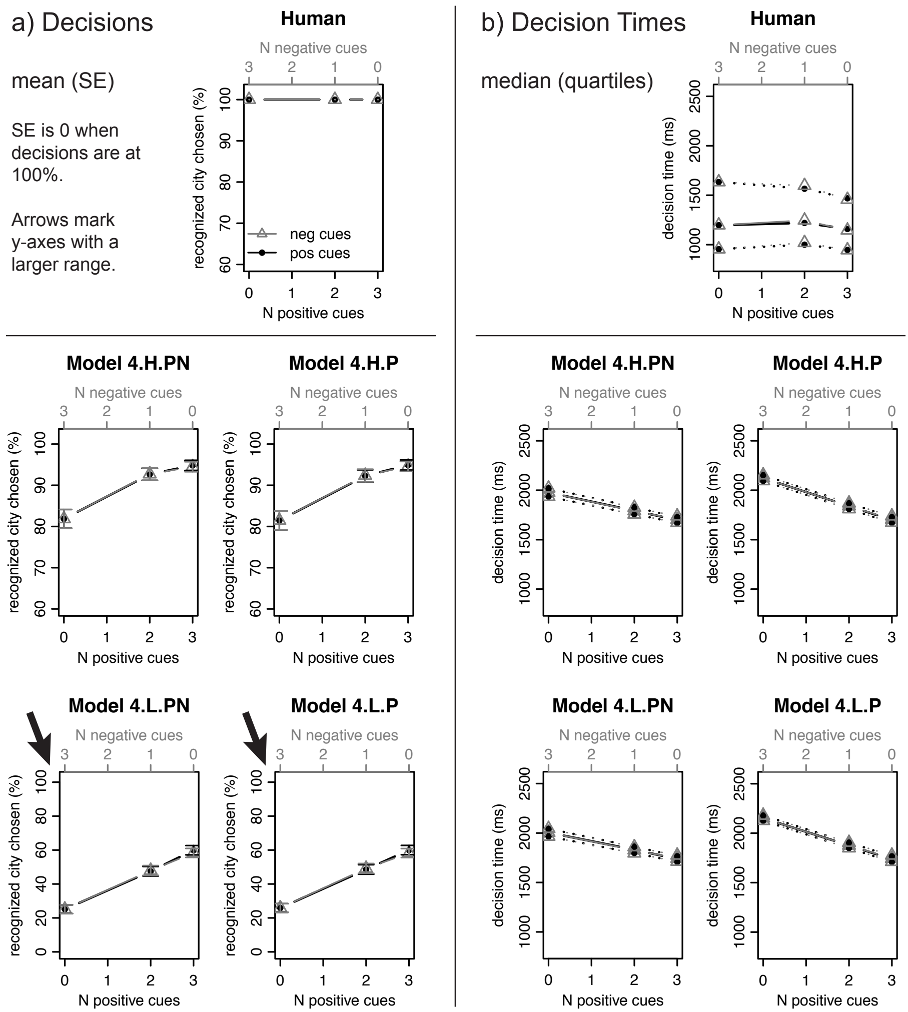


Figure 5.C23 Model 4 class and human data—recognition group – Experiment 2.

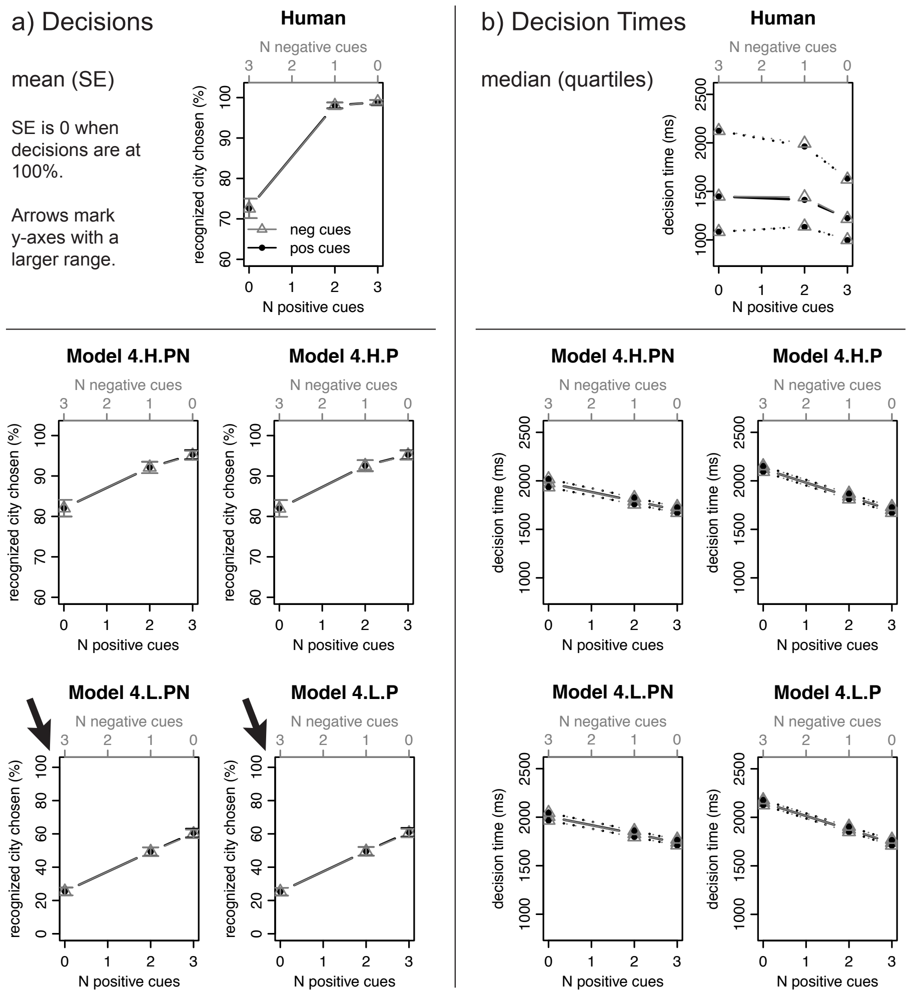


Figure 5.C24 Model 4 class and human data—cue group—Experiment 2.

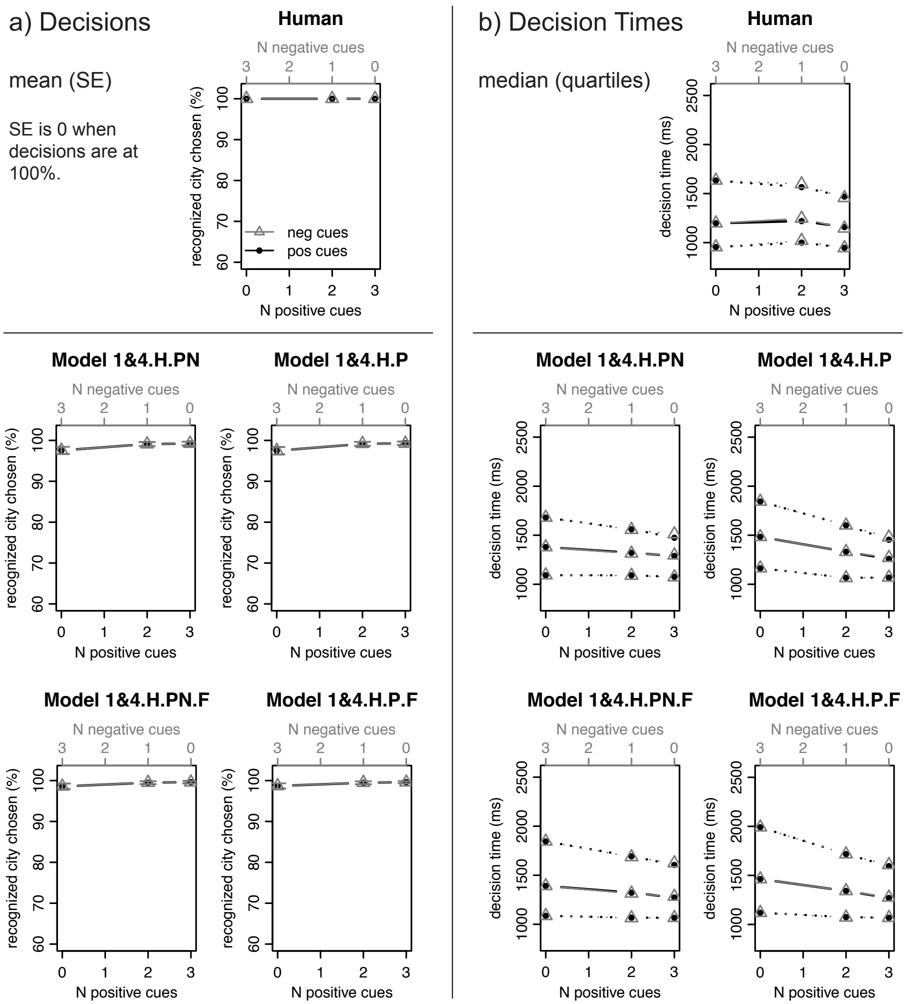


Figure 5.C25 Model 1&4.H class and human data—recognition group—Experiment 2.

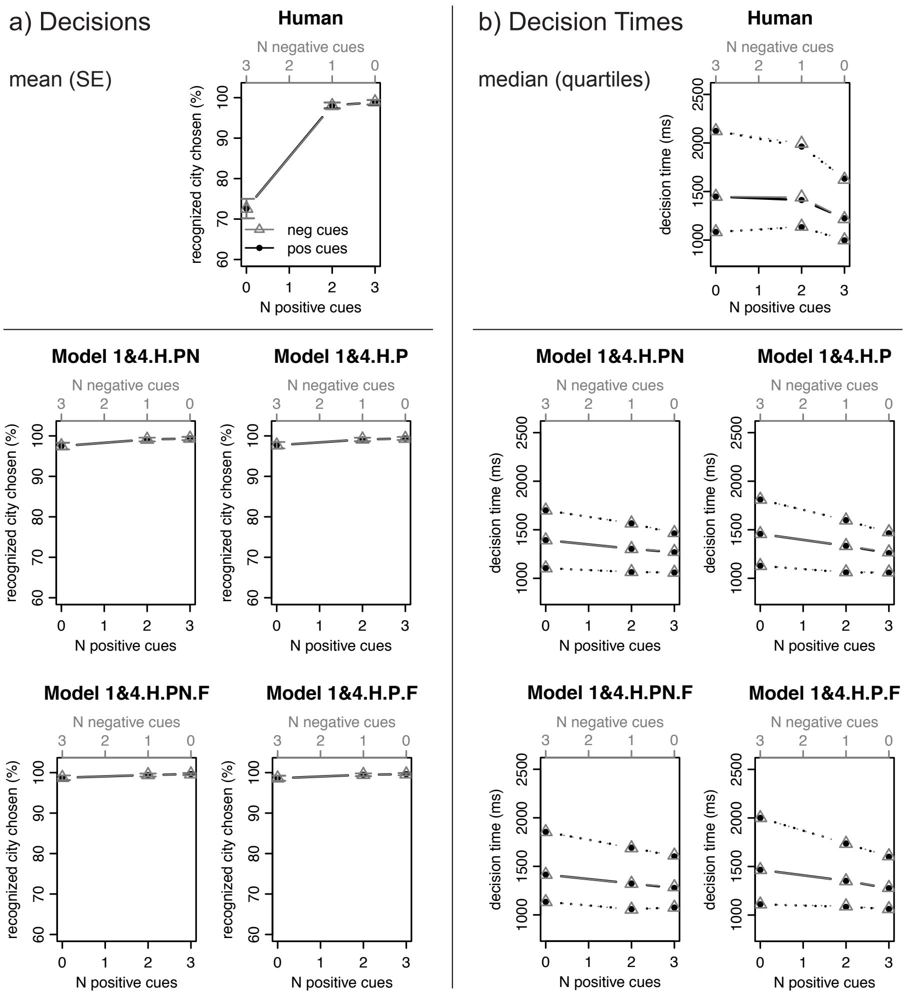


Figure 5.C26 Model 1&4.H class and human data—cue group—Experiment 2.

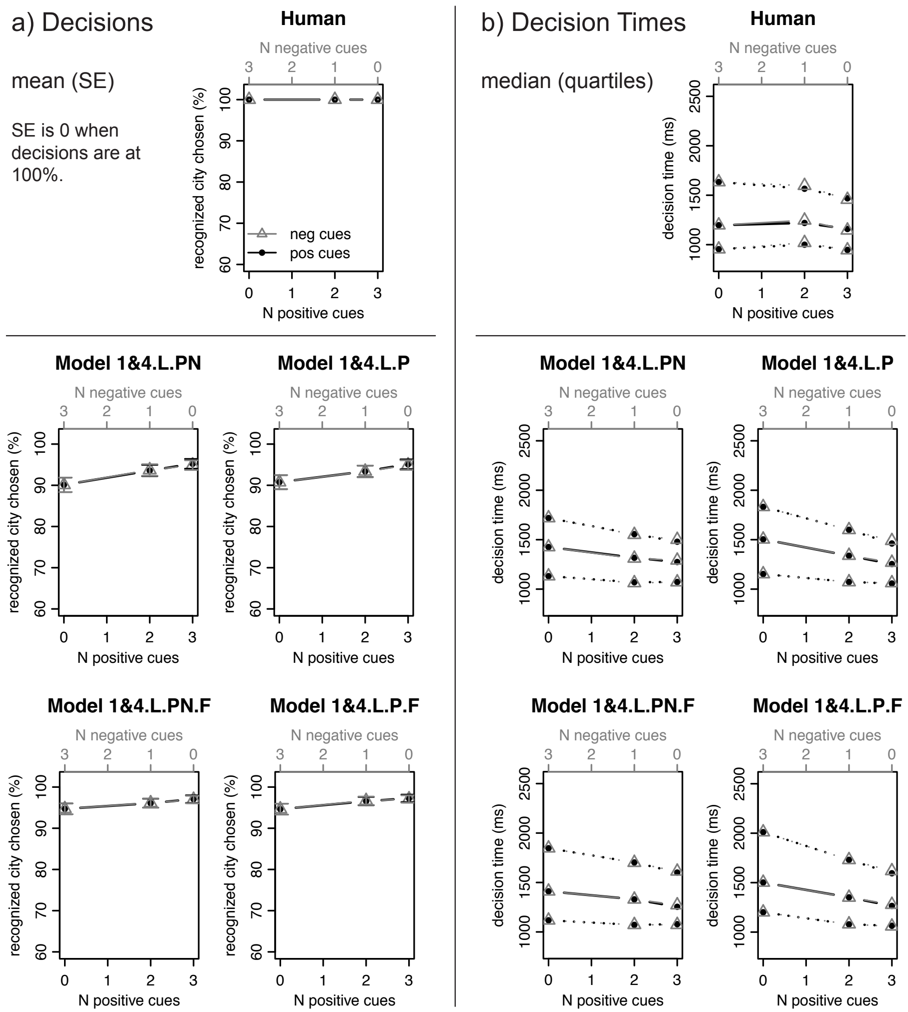


Figure 5.C27 Model 1&4.L class and human data—recognition group—Experiment 2.

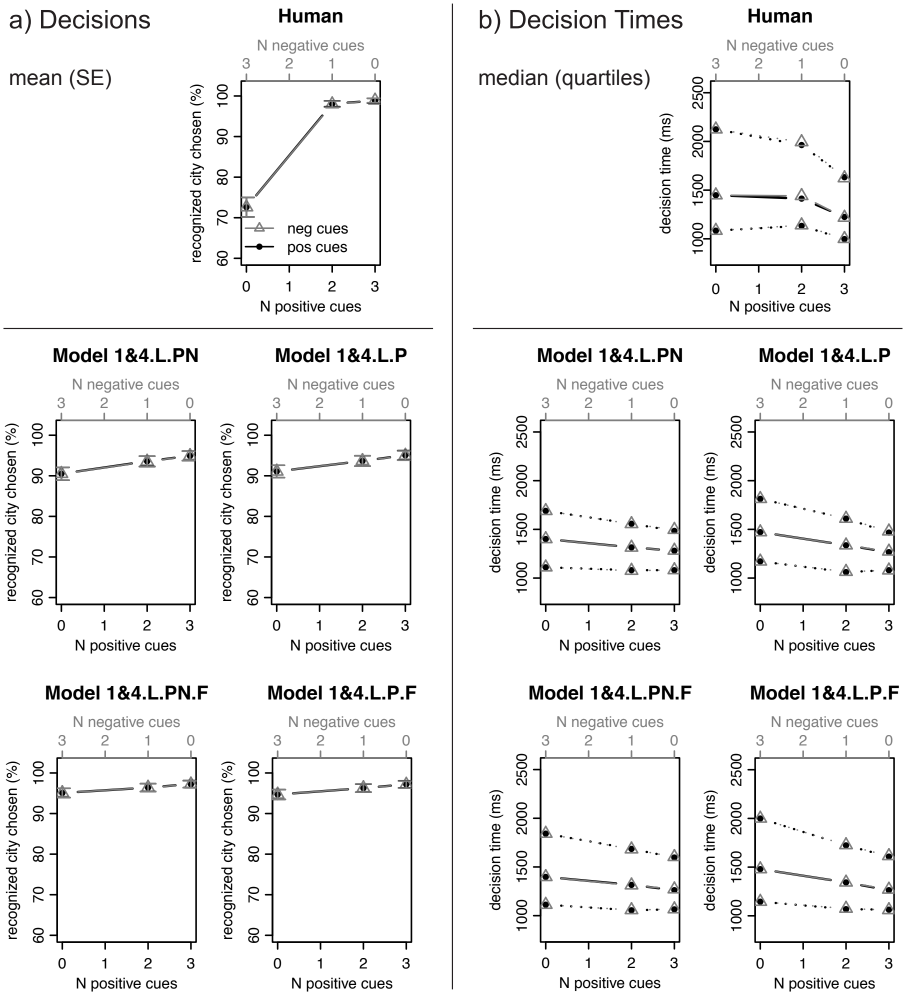


Figure 5.C28 Model 1&4.L class and human data—cue group—Experiment 2.

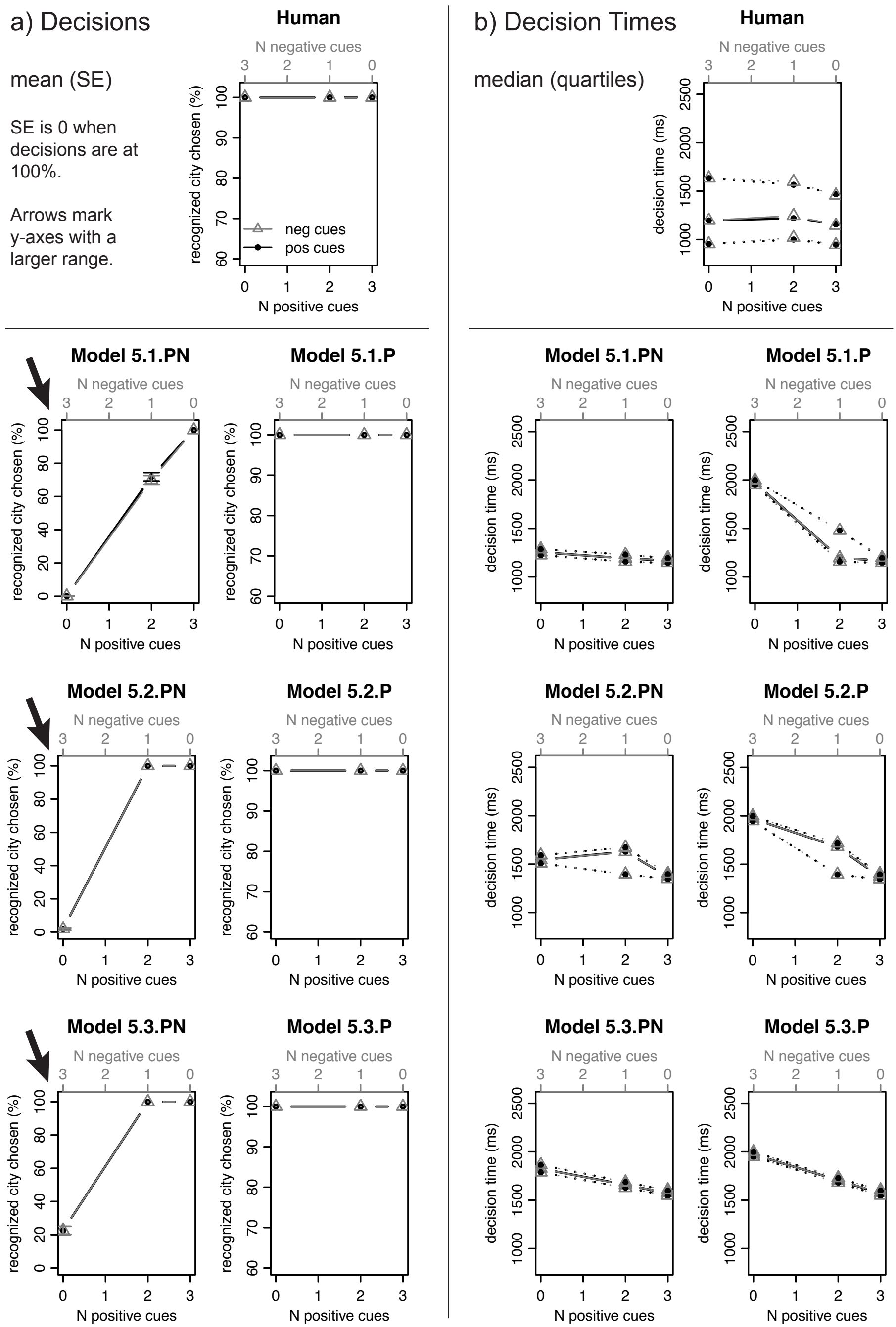


Figure 5.C29 Model 5 class and human data—recognition group – Experiment 2.

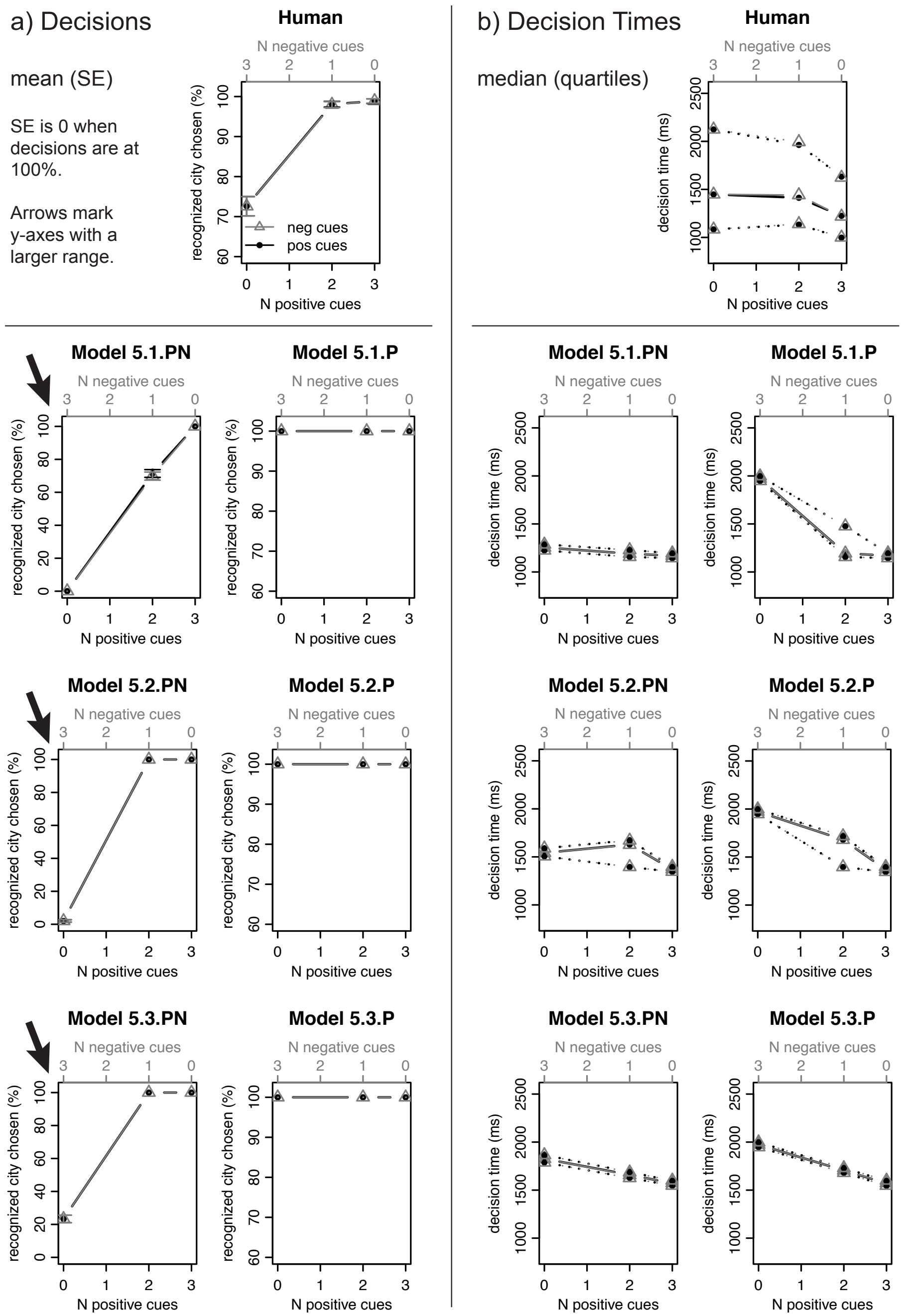


Figure 5.C30 Model 5 class and human data—cue group—Experiment 2.

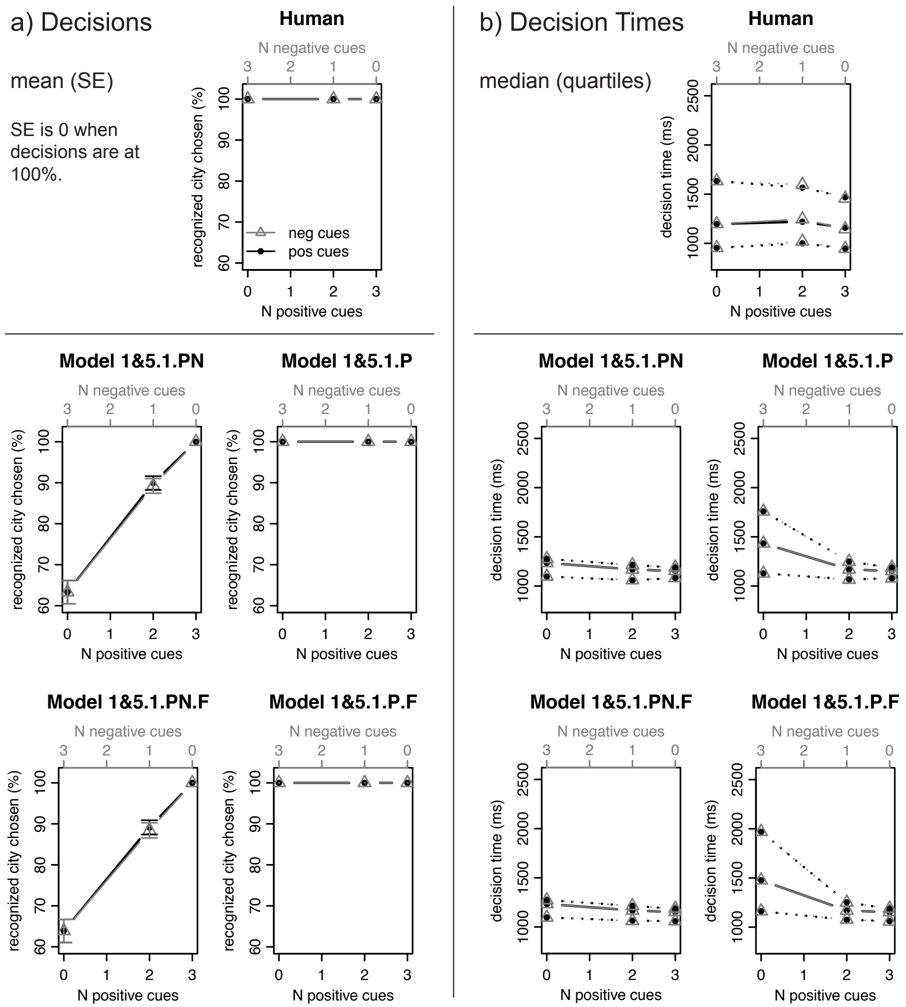
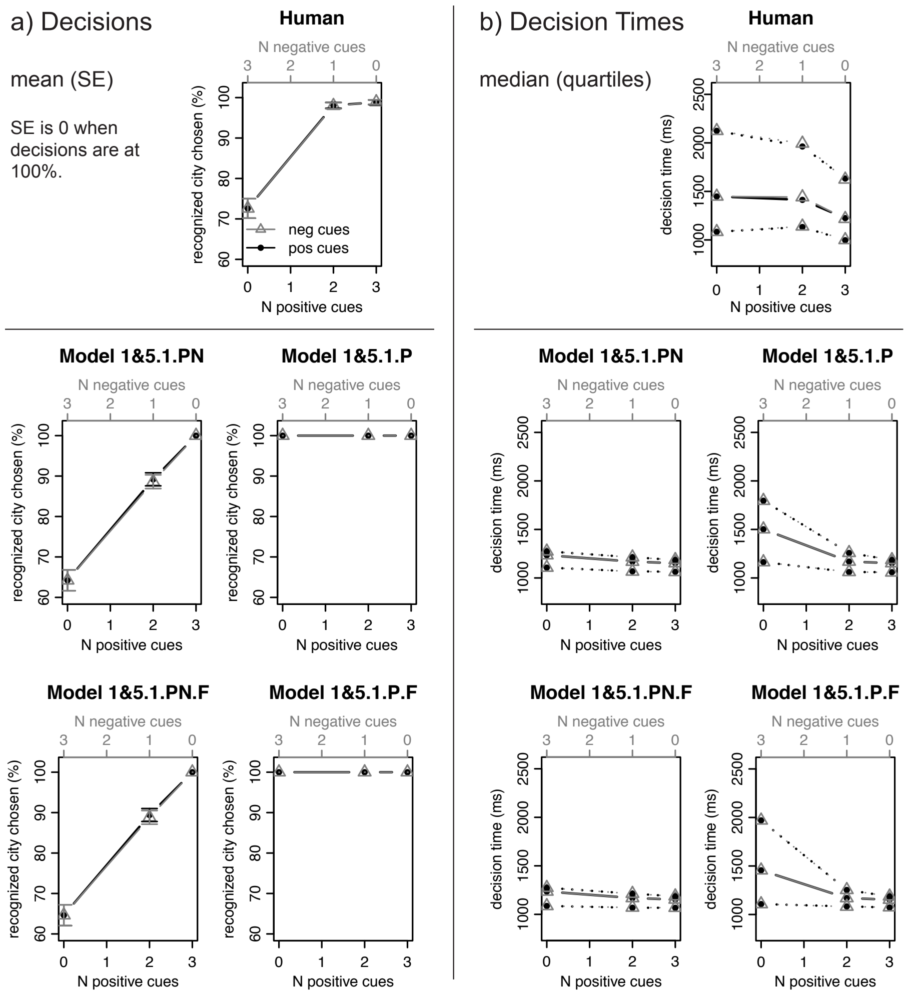


Figure 5.C31 Model 1&5.1 class and human data—recognition group—Experiment 2.



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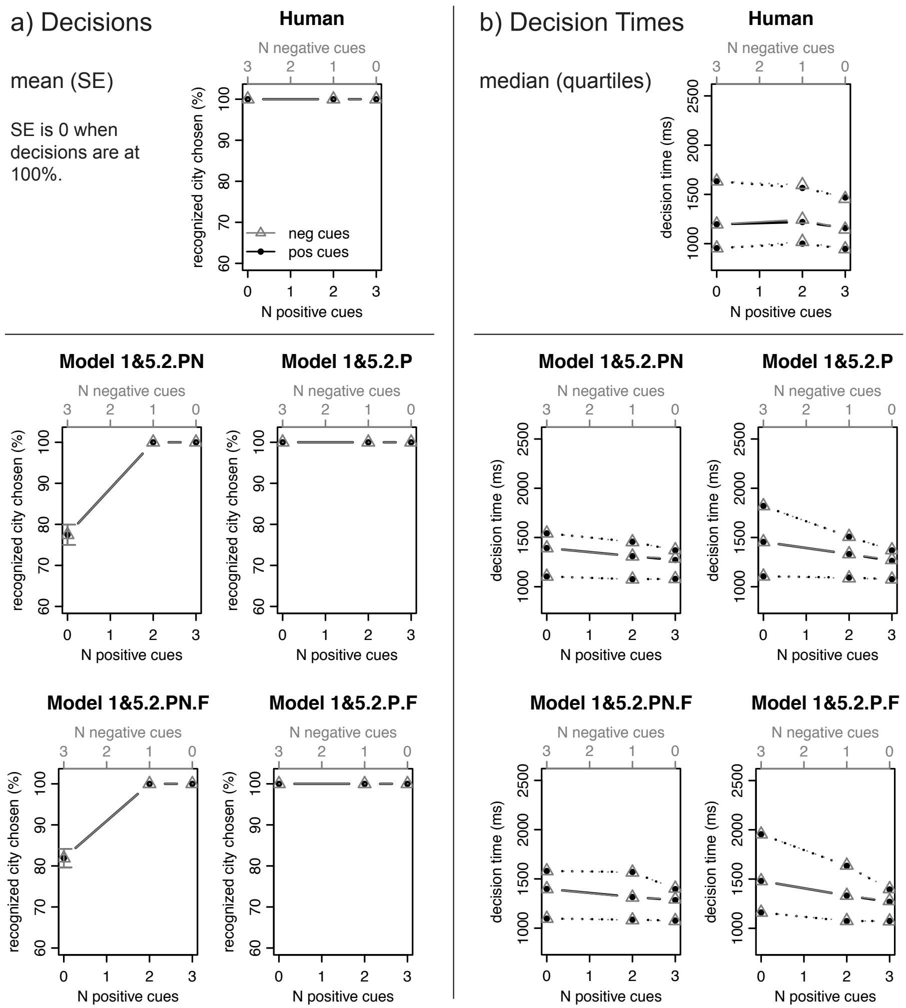

Figure 5.C33 Model 1&5.2 class and human data—recognition group—Experiment 2.

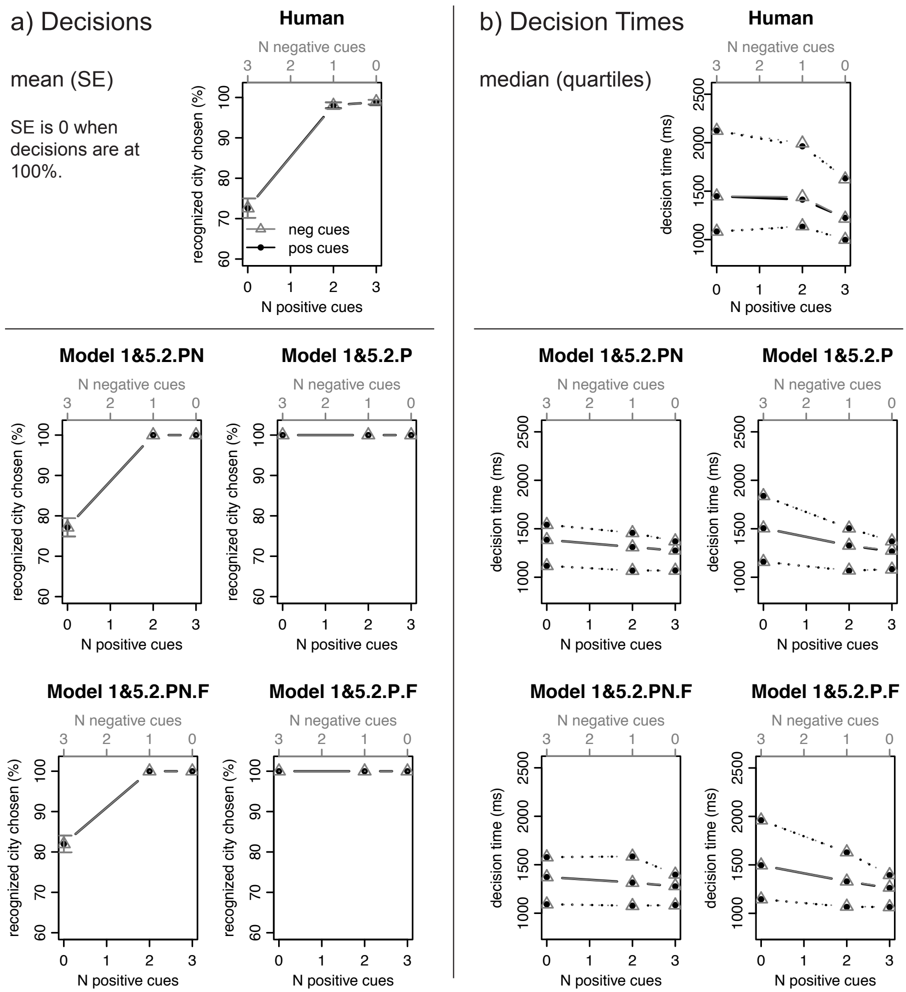

Figure 5.C34 Model 1&5.2 class and human data—cue group—Experiment 2.

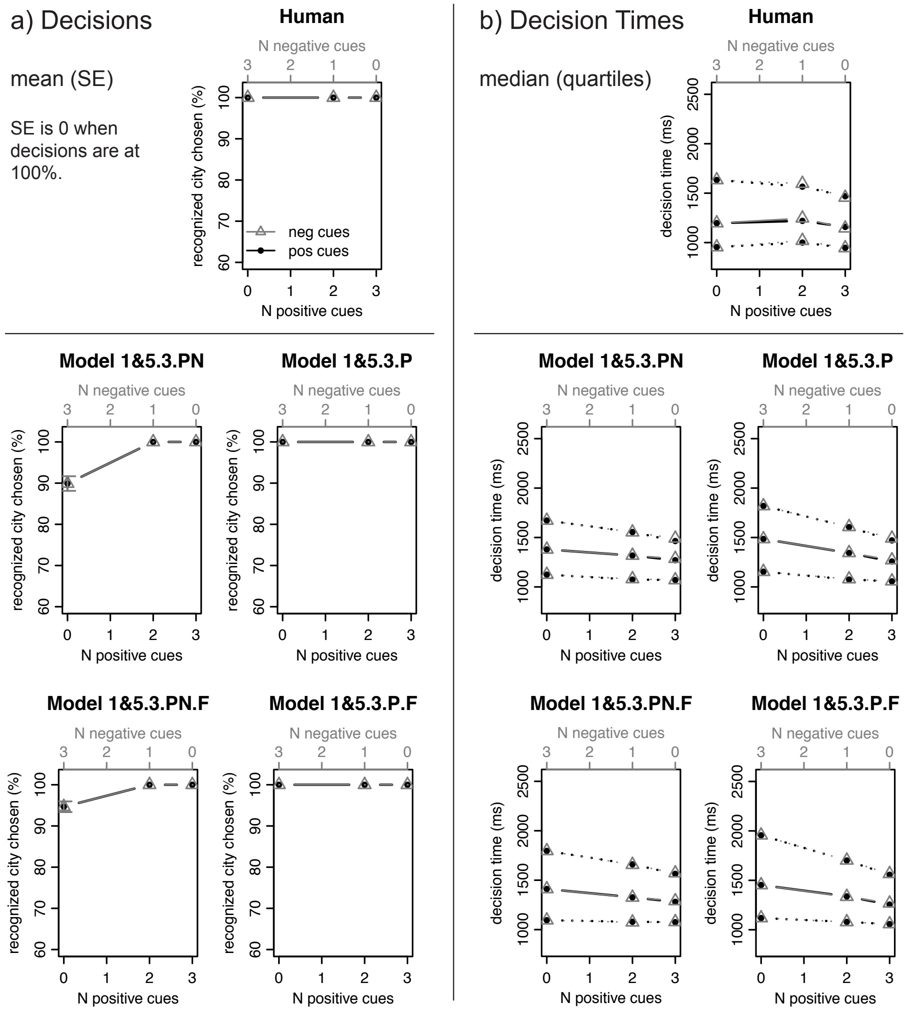

Figure 5.C35 Model 1&5.3 class and human data—recognition group—Experiment 2.

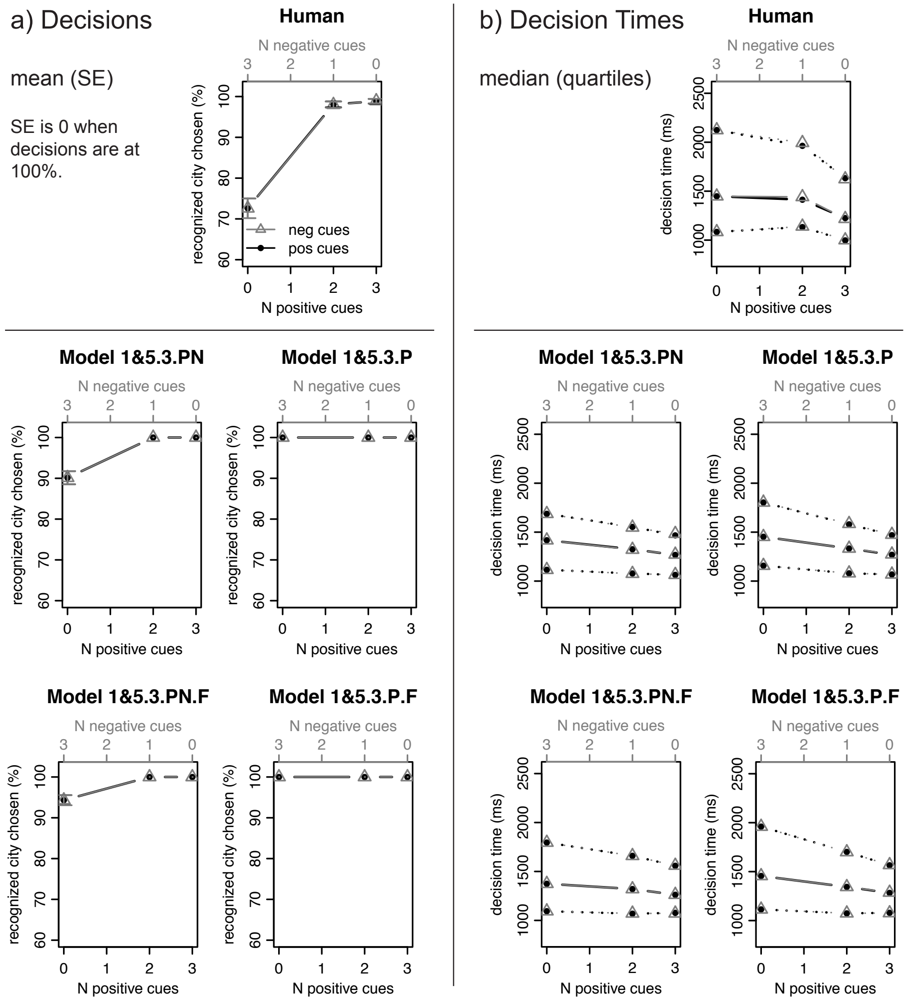

Figure 5.C36 Model 1&5.3 class and human data—cue group—Experiment 2.