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THEORETICAL/REVIEW

Value-driven attention and associative learning models: a computational simulation analysis

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Abstract
Value-driven attentional capture (VDAC) refers to a phenomenon by which stimulus features associated with greater reward value attract more attention than those associated with smaller reward value. To date, the majority of VDAC research has revealed that the relationship between reward history and attentional allocation follows associative learning rules. Accordingly, a mathematical implementation of associative learning models and multiple comparison between them can elucidate the underlying process and properties of VDAC. In this study, we implemented the Rescorla-Wagner, Mackintosh (Mac), Schumajuk-Pearce-Hall (SPH), and Esber-Haselgrove (EH) models to determine whether different models predict different outcomes when critical parameters in VDAC were adjusted. Simulation results were compared with experimental data from a series of VDAC studies by fitting two key model parameters, associative strength (V) and associability (α), using the Bayesian information criterion as a loss function. The results showed that SPH-V and EH- α outperformed other implementations of phenomena related to VDAC, such as expected value, training session, switching (or inertia), and uncertainty. Although V of models were sufficient to simulate VDAC when the expected value was the main manipulation of the experiment, α of models could predict additional aspects of VDAC, including uncertainty and resistance to extinction. In summary, associative learning models concur with the crucial aspects of behavioral data from VDAC experiments and elucidate underlying dynamics including novel predictions that need to be verified.

Keywords Value-driven attentional capture · Associative learning · Computational simulation · Mathematical implementation · Model comparison

Introduction

Selective attention is the process of selecting particular stimuli for further processing (Treisman, 1964). In the literature on attention, growing evidence denotes that stimuli associated with larger rewards attract more attention involuntarily than those associated with smaller rewards. This phenomenon is referred to as value-driven attentional capture (VDAC; Anderson et al., 2011b). Here, VDAC is considered to incorporate associative learning within its core mechanism due to the direct association between stimuli and rewards. Importantly, however, multiple interpretations from different, often opposing, models elucidate associative learning. Furthermore, the extent to which the way learning modifies VDAC is comparable to associative learning is unclear, given that factors other than reward magnitude influence the stimulus–reward associations identified in nonhuman animal research. Thus, it is necessary to investigate which associative learning model best describes VDAC and which learning-related factors, other than the magnitude of reward, influence the underlying dynamics of VDAC.

In a classical VDAC paradigm, the stimulus–reward association occurs during a training phase, which is then followed by a test phase that reveals the attentional priority for stimuli previously associated with a high reward value

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compared to those previously associated with either a low or no reward value (Anderson & Halpern, 2017; Anderson et al., 2011b; Bucker & Theeuwes, 2017; Mine & Saiki, 2015). For instance, in a study by Anderson et al. (2011b), participants were instructed to search for either a red or green circle among heterogeneously colored circles in the training phase. Specifically, one of the two target colors was paired with a higher reward contingency, which comprised an 80% chance of providing a high reward (e.g., 5 cents) and a 20% chance of providing a low reward (e.g., 1 cent), and vice versa for the other target color. In the subsequent test phase, participants were instructed to search for a unique shape (i.e., a diamond among circles, a circle among diamonds). One distractor was rendered in the reward-associated color (i.e., red or green with an equal probability) in half of the trials. Importantly, responses were slower when the distractors previously associated with the high reward were presented than when the distractors associated with the low reward were presented. This signifies that the magnitude of the associated reward modulates the allocation of attention (Anderson et al., 2011b). Given that attentional capture by a task-irrelevant stimulus led to inefficient search, VDAC is generally assumed to follow Pavlovian conditioning (i.e., the extent to which a stimulus predicts reward) rather than instrumental learning (Bucker & Theeuwes, 2017; Le Pelley et al., 2015).

Pavlovian conditioning, one of the primary forms of associative learning, involves the presentation of two stimuli temporally and spatially close together. Modern theories emphasize the role of prediction error, which is the difference between an event's expected and actual outcomes (Holland & Schiffino, 2016). One class of implementation, such as the Rescorla-Wagner (RW) model, operates by directly reassigning the acquired strength of the association (associative strength; V) using the prediction error computed with the received value of a reinforcer or punisher.

Meanwhile, other implementations that also consider the effectiveness of the pairing, argue that the prediction error also changes the associability (α) of conditioned stimuli. The models in this class include Mackintosh (Mac) and Pearce-Hall (PH) formulation and share the characteristic that the α is adjusted through exposure to a stimulus. Thus, this class of models explain many more learning phenomena than the models described in the previous paragraph. The α plays a part in several learning phenomena, as seen by latent inhibition (Lubow & Moore, 1959), which manifests as a retarded pairing when a stimulus is repeatedly delivered prior to the conditioning without altering the V (Wagner & Rescorla, 1972).

Importantly, Pavlovian conditioning encompasses a multitude of factors, other than V and α, such as predictiveness, and uncertainty (Koenig, Kadel, et al., 2017a; Koenig, Uengoer, et al., 2017b; Le Pelley et al., 2019). Thus, interpreting VDAC using the Pavlovian conditioning paradigm requires an investigation of how each factor – either alone or through interaction with other factors – modulates the dynamics of the effect. Applying the mathematical implementations of learning models on VDAC would be an effective way to investigate these factors and to explain fundamental cognitive mechanisms that behavioral data fail to disclose. However, to the best of our knowledge, only a few studies have attempted to interpret VDAC with associative learning models (Le Pelley et al., 2016; Le Pelley et al., 2019), and none have conducted a detailed comparison of how various models explain the behavioral data obtained from the VDAC literature.

Therefore, to advance our understanding of VDAC, the aim of the present study was to examine behavioral phenomena observed in the literature by comparing the simulated results of representative associative learning models. Four major associative learning models – RW, Mac, Schmajuk-Pearce-Hall (SPH), and Esber-Haselgrove (EH) – were employed and tested to determine which is most applicable to explain VDAC observed in human studies. The outputs of V and α obtained from simulations were quantitatively compared to the behavioral results from the VDAC literature by utilizing the Bayesian information criterion (BIC) and negative log-likelihood.

Four factors were considered critical in VDAC: *expected value (EV), training session, uncertainty, and switching.* We selected these factors to confirm basic phenomena in VDAC and differentiate each associative learning model based on their core assumptions. By comparing the simulated predictions from different associative learning models and the existing behavioral data for each factor, the aim of the present study is to determine the learning models most suitable for elucidating value-driven attention.

Learning-related factors in value-driven attention

Expected value

EV, which is calculated by multiplying each of the possible outcome values by the probability of each outcome and summing all of the values, is assumed to be the most fundamental factor that determines the strength of VDAC. As the EV associated with a stimulus feature increases, the associative strength between the stimulus feature and value also increases, consistent with VDAC.

Although VDAC has been observed mostly within the visual domain (see Anderson, 2016a, for a review), VDAC is also present in the auditory domain (Anderson, 2016b). In the training phase, participants were asked to press the space bar when they heard “A” or “Y.” A response to one target sound resulted mostly in a high reward, while a response to the other target resulted mostly in a low reward. In the test phase without reward, the target and nontarget sounds served as distractors during a visual search task. Responses for the visual search were delayed when the sound frequently associated with the high reward was played compared to when the sound frequently associated with the low reward was played. This result indicates that the sound associated with the high reward captured more attention than the other sound. Thus, the study showed that VDAC also operates in the auditory domain.

In addition, although most VDAC experiments have used the visual search task in both the training and the test phases, Mine and Saiki (2015) confirmed VDAC via a flanker–compatibility task in the training phase, in which a target letter was presented in the center of the screen with nontarget letters (flanker letters) presented on the left and right sides of the target. The colors of the flankers predicted rewards (e.g., red flankers frequently yielded high reward and the green flankers frequently yielded low reward). In the test phase, the high reward color distractors delayed the search more than the low reward color distractors, indicating that the high reward color distractors captured attention more than the low reward color distractors. These imply that VDAC is easily generalized to different tasks. Hence, the presence of VDAC across different sensory modalities and tasks increases the generalizability of the effect of EV in the allocation of attention.

Training session

Most previous studies using the classical VDAC paradigm failed to observe a statistical difference in behavioral performances between the target types in the training phase (Anderson & Halpern, 2017; Kim & Beck, 2020; Miranda & Palmer, 2014; Roper & Vecera, 2016). These results are possibly due to a ceiling/floor effect: while reward feedback allowed participants to adequately form stimulus–reward associations, top-down attentional control may have modulated the visual search for the two target colors by assigning equal priority (Anderson et al., 2013), as the reward itself was irrelevant to identifying the line orientation within the target circles. The attentional control required to maintain the task goal may be too strong to statistically render value-driven attention by implicit learning.

Specifically, Anderson et al. (2011a) provided a fine-grained analysis of behavioral performance across target types. They divided the training phase into ten bins of (approximately) 100 trials and examined how the effect of reward on target selection changed over the course of the training phase. Similar to the studies previously mentioned, Anderson et al. (2011b) failed to obtain a significant main effect of target type, again confirming that the operation of attentional control is too strong to statistically detect the attentional bias driven by incidental learning. Notably, however, the numerical differences in search performance between the high- and low-reward targets showed a steep increasing trend, peaking in the third (i.e., 201–300 trials) and fourth (i.e., 301–400) bins, followed by a gradual decline in the latter half of the training phase. Although the interaction between target type and trial bin failed to reach significance, we considered that such a numerical trend demanded further investigation.

Switching and inertia

Previous studies have confirmed that VDAC resists extinction even over the course of several hundred unrewarded trials (Anderson & Yantis, 2013; Della Libera & Chelazzi, 2009; Stankevich & Geng, 2014). Although the classical conditioning theory of learning proposed that a previously conditioned response to a reward-predictive stimulus will vanish in the absence of reinforcement (Pavlov, 1927; Wagner, 1961), most studies on VDAC have shown no significant reduction in attentional capture by the reward-related distractors in the test phase (Anderson et al., 2011b; Anderson & Yantis, 2012, 2013; Bucker et al., 2015; Failing & Theeuwes, 2014; Rothkirch et al., 2013; Sali et al., 2014; Stankevich & Geng, 2014; Theeuwes & Belopolsky, 2012). These findings suggest that reward learning generates a persistent attentional priority in favor of the previously reward-associated feature even when no longer predictive of reward (Milner et al., 2023).

Liao and Anderson (2020) investigated how a previously formed reward association influences the subsequent updating of attentional allocation in response to changes in reward contingencies. They reversed the reward contingencies of two stimuli (i.e., high and no reward) in the middle of the experiment without instruction, which led to the acquisition of value for the new high-reward distractor and extinction for the old high-reward distractor. Importantly, the residual attentional bias toward the old high-reward target stimulus persisted during the training phase and even during the test phase when it served as a distractor. The results indicated that VDAC does not quickly update with new reward learning and lingers even after value-reversal. These findings further substantiate the stability and the persistence of VDAC demonstrated in the previous literature (Anderson & Yantis, 2013).

Uncertainty

VDAC is also influenced by how well a cue predicts a reward, or, put another way, by the degree of uncertainty around this correlation (Le Pelley et al., 2016). However, there are two seemingly contradictory models: the predictiveness-based principle (Mackintosh, 1975) and the uncertainty-based model (Pearce & Hall, 1980). According to the predictiveness principle (Mackintosh, 1975), attention prioritizes cues that reliably predict subsequent events to exploit known stimulus–outcome relationships (Easdale et al., 2019; Le Pelley, 2004; Le Pelley et al., 2013; Mitchell & Le Pelley, 2010). According to the uncertainty-based model (Pearce & Hall, 1980), attention is preferentially deployed for cues when outcomes are uncertain, thereby reducing the uncertainty regarding the stimulus–outcome association.

In general, the uncertainty principle has been supported in the VDAC literature. For example, Cho and Cho (2021) explored whether certain and uncertain rewards influence VDAC differently. As in a typical VDAC experiment (Anderson et al., 2011b), the experiment had a training phase and a test phase. In the training phase, search targets were red and green. One color yielded uncertain rewards: 100 points for 25% of the trials and 0 points for 75% of the trials. The other color yielded certain rewards: 25 points for all trials. Therefore, the EVs of the certain and uncertain colors were identical, but the certainty of the predicted rewards differed. In the test phase, the search target was a diamond among heterogeneously colored circles. In some trials, one of the circles was either the certain-related color or the uncertain-related color. The search was delayed longer for cases with the uncertain-related color distractor than for those with the certain-related color distractor. In summary, VDAC was larger for the distractor associated with uncertain rewards than for the distractor associated with certain rewards even when the EVs were kept identical.

Le Pelley et al. (2019) investigated whether VDAC is influenced by the consistency with which stimuli signaled a particular magnitude of reward. In their Experiment 1, participants were asked to make an eye-movement toward a diamond-shaped target among circles. Three distractor colors were related to the amount of reward: two colors consistently predicted a high reward and a low reward, and another color yielded low and high rewards with equal probability. Unlike other experiments, there was no separation between training and testing sessions, and one or two of the three colors were presented in every trial. The results showed that (1) gaze on the high-value color was more probable than other colors, and (2) the probability of gaze on the nonpredictive color was numerically higher than that of low-value color. These findings suggest that the EVs of the colors influence VDAC, while predictiveness has little influence on VDAC.

Furthermore, eye-gaze data from Experiment 2 demonstrated that participants' gazes and first saccades were directed more strongly toward nonpredictive than predictive distractors. In a similar vein, Koenig, Kadel, et al. (2017a) showed that the duration of gaze fixation was longer for stimuli associated with uncertain rather than certain rewards. These findings suggest that in addition to EV, uncertainty also influences value-driven attention and supports the uncertainty-based model in VDAC.

Simulation experiments

Methods

We selected four associative learning models in this study: the RW, Mac, SPH, and EH models. All have two terms in their core structure: V and α. The V shows the extent to which the stimulus predicts the upcoming unconditioned stimulus (US). Conversely, α determines how fast the association between two stimuli is formed. A large body of research denotes α with various names, including learning rate parameter (Rescorla & Wagner, 1972), acquired saliency (Esber & Haselgrove, 2011), or, more frequently, attention (Le Pelley et al., 2019). However, we refrain from using cognitively interpreted terms; instead, we use α as associability in the present study. To compare which output value – V and α – best describes VDAC, we generated two sub-models (V model and α model) from each model (RW, Mac, SPH, EH) and treated them as separate models in this study. Therefore, a total of eight models were included in this study.

Since 1970, associative learning theories have incorporated the concept of learning ability based on expectancy violation. First introduced by Bush and Mosteller (1955), expectancy violation is calculated as the discrepancy between expectation and the actual outcome. Rescorla and Wagner (1972) developed this idea so that the change in V at trial t (ΔV_t) is proportional to the difference between the sum of expectations ($\sum_{CS \in t} V_t$) and the US (λ). They also included two constants, α and β, each representing the learning rate and the physical intensity of the stimulus and formulated the RW model (Eq. 1).

$$\Delta V_t^s = \begin{cases} \alpha\beta^s\left(\lambda_t - \sum_{CS\ s' \in t} V_t^{s'}\right) & , \ \mathit{if}\ \text{CS}\ s \in \text{Trial}\ t \\ 0 & , \quad \mathit{otherwise} \end{cases} \tag{1}$$

Such an implementation explained a broad range of experimental findings from animal experiments and quickly became the most influential theory in associative learning. Here, we included the RW model as a baseline model as the model assumes constant α throughout learning.

Next, we selected two contradictory models, the Mac and PH models, both of which have α adjustment mechanisms. They differ in the rules they propose for predicting how the α changes if the outcome associated with the stimulus is not stable. The Mac model proposed that α is determined by how correctly a stimulus predicts the US. The model proposed that the conditioned stimulus (CS) s's α ($\Delta\alpha_t^s$) at the trial t is controlled by the discrepancy between the observed and the predicted US according to the following rule:

$$\begin{cases} \Delta\alpha_t^s > 0, & D_t^s < D_t^{\neg s} \\ \Delta\alpha_t^s < 0, & D_t^s \geq D_t^{\neg s} \end{cases}, \tag{2}$$

where D represents the amount of discrepancy defined as:

$$\begin{aligned} D_t^s &= |\lambda_t - V_t^s| \\ D_t^{\neg s} &= \left|\lambda_t - \left\{\left(\sum_{CS\, s' \in t} V_t^{s'}\right) - V_t^s\right\}\right| \end{aligned} \tag{3}$$

In contrast, the PH model states that if the stimulus perfectly predicts the US, no further α is required as the learning has already reached its asymptote. In this sense, the α of the model relies only on the prediction error, defined as

$$\alpha_{t+1} = \left|\lambda_t - \sum_{CS\, s' \in t} \dot{V}_t^{s'}\right|, \tag{4}$$

where $\dot{V}_t$ represents the expected intensity of the US on trial t. Another important characteristic of the PH model that differs from the Mac model is the separation of inhibitory learning. The model incorporates the idea of no-US representation by Konorski (1967) and uses a term representing the absence of the US, $\overline{V}$, in inhibitory conditioning. The value of $\overline{V}$ increases when the expected intensity of the US is larger than its actual intensity. Since there are two V values for each stimulus – excitatory and inhibitory – the expected US intensity at trial t is calculated as follows:

$$\dot{V}_t = \sum_{CS\, s' \in t} \left(V_t^{s'} - \overline{V}_t^{s'}\right). \tag{5}$$

However, we had to refer to other studies for our quantitative simulations for the following reasons. First, Mackintosh (1975) did not formalize a complete model; instead, he proposed the α update rule. Therefore, in the present study, we used the modified implementation of the Mac model by Moore and Stickney (1980). The Mac model implementation uses a similar structure to the RW model (Eq. 1), but the α is changed according to the following rule:

$$\Delta\alpha_t^s = \begin{cases} k\left(1-\alpha_t^s\right)\left(D_t^{\neg s} - D_t^s\right)/2, & D_t^s < D_t^{\neg s} \\ -k\epsilon, & D_t^s = D_t^{\neg s} \\ k\alpha_t^s\left(D_t^{\neg s} - D_t^s\right)/2, & D_t^s > D_t^{\neg s} \end{cases}. \tag{6}$$

The constant rate parameter, k, acts as a learning rate and two terms – $\left(1-\alpha_t^s\right)$ and α_t^s – are incorporated to impose "the law of diminishing returns." We modified the implementation of Moore and Stickney (1980) with an additional ϵ parameter, which represents a small positive number to decrease the α when the two discrepancies are equal.

Second, the α formalized by Pearce and Hall (1980) does not incorporate the concept of momentum in formulating α. A learning schedule where the presented US is stable during a certain number of trials does not cause a problem in the simulation. However, if the presence or intensity of the US changes during the learning schedule, α without momentum can vigorously fluctuate. Accordingly, here we used a modified version of the PH model developed by Schmajuk and Moore (1985) that introduced momentum as follows:

$$\alpha_t = \gamma\left|\lambda_t - \dot{V}_{t-1}\right| + (1-\gamma)\alpha_{t-1}, \tag{7}$$

where γ modulates the magnitude of the momentum. In this way, the fluctuation of the α value can be moderated.

Finally, we chose the EH model (Esber & Haselgrove, 2011) as an example of a hybrid model, which incorporates multiple stimulus-processing modules. Although there are a large number of hybrid models ranging from a simple model that uses combined α from the Mac and PH models (Le Pelley, 2004) to models that have more than two modules (George & Pearce, 2012; Schmajuk et al., 1996; Wagner, 1981; Wagner & Brandon, 1989), we included the EH model because of its mathematical and systemic simplicity. The EH model is an intermixed model that incorporated several aspects of the Mac and the PH model. The α of the model proportionally increases with the expectancy ($V_t + \overline{V}_t$) as in the Mac model, and the model uses separate terms for inhibitory conditioning, $\overline{V}$, as in the PH model. In addition, the model included a negative term in the α to account for latent inhibition, and used separate learning rate parameters for excitatory and inhibitory conditioning. Because of the similarity between this and the other models, it was easy to compare simulation results between models. The detailed mathematical implementation of all models used in this study is presented in the Online Supplementary Material (OSM; S1: Model implementation).

Simulation

We employed maximum likelihood estimation to calculate the goodness of fit of each model. To calculate the maximum likelihood, we require two probability distributions, one from human experimental data and the other from the model. The best method for generating a probability distribution for experimental data would be building a nonparametric probability distribution from raw data. However, due to the simplicity, we assumed that behavioral indices follow a Gaussian distribution; therefore, we generated artificial distributions of experiments using values presented in the studies. First, we selected one behavioral index from an experiment, such as response time (RT) or proportion of eye fixation. Then we used the difference between the target's and the control's behavioral index (ex. [RT of Stimulus 1] - [RT of Control Stimulus]) as the mean of the distribution. We used a fixed value of 3 for the standard deviation after confirming that this would not alter the relative goodness of fit between the models' simulations (OSM, S2: Effect of experiment's SD on simulation results). We used the RW-α model (constant VDAC for all stimuli) as a baseline and ordinally compared models' performances. Next, we simulated each experiment to generate a probability distribution for the model. The simulation mimicked the experiment, including the stimulus composition and the total numbers of training and testing trials. As for the reward in experiments, we used the relative ratio of different reward types for the simulation. For instance, if an experiment has two reward types with values of 500 points and 50 points, we set the intensity of the US (λ) as 1 and 0.1, respectively. We also used 200 randomly shuffled experiment schedules because the order of stimulus presentation alters the behavior of models. We used a linear transformation to directly compare simulation results with behavior indices. In this procedure, a model's output, V or α, was transformed into the corresponding behavior index, such as milliseconds (ms) for RT and percentage (%), by following the equation.

$$\text{behavior index (RT, \%)} = w \cdot \left(\text{model's output}\right) + b$$

These two linear transformation parameters – weight, *w*, and bias, *b* – were also added to the optimization algorithm to find the best match that maximizes the likelihood. Finally, we calculated how likely these transformed values could be observed from the probability distributions of participants' behavior data. We used the negative log-likelihood as a loss function to find the model and the linear transformation parameters. We wrote custom MATLAB scripts that implement the sequential quadratic programming algorithm to find the optimal parameters. In addition, we used the MultiStart function with 60 different initial parameter sets to discover the global minima. All MATLAB scripts, along with the UI-based model simulator, can be downloaded from Github (https://github.com/knowblesse/Modeling).

Model comparison

We compared the goodness-of-fit between models based on the BIC score calculated for each model. As the RW-α model assumes stable attentional allocation to all stimuli, we used the performance of this model as a baseline for the model comparison. Then we calculated the BIC value ratio of the remaining associative learning models. Among the seven models, we selected three models with the lowest BIC value ratio and marked them bold in the tables. If a model's BIC value ratio exceeded 1, this was also marked in the tables as this could be interpreted as the model prediction being contrary to the experimental results.

Results

Expected value

First, we compared the simulation results of four studies (Anderson, 2015; Anderson & Halpern, 2017; Anderson et al., 2011b; Mine & Saiki, 2015) with a similar experimental paradigm to observe the general properties of each associative learning model. These studies used two stimuli that differ in the EV of the associated reward. The simulation results from all models showed a typical growth curve during training sessions in which stimuli were associated with rewards. During testing sessions, previously rewarded stimuli acted as distractors without a reward, resulting in a slow extinction curve. Notably, regardless of the model type, V or α, all simulations predicted stronger VDAC for the stimulus associated with a higher EV than one associated with a lower EV (representative examples are presented in Fig. 1; the other three models showed a similar result).

Next, we observed that the asymptote values of models during training sessions varied across simulated experiments. We found that as the ratio of EVs between two stimuli increased the asymptote differences widened (Table 2). Especially, the experiment by Anderson (2015), which used a 10-cent reward for one stimulus and no reward for the other, reported the highest asymptote difference among all experiments (Figs. 1A and 2A). Since V reflects the strength of association, these characteristics were more evident in V models than in α models.

In addition, as one of the studies (Anderson et al., 2011b) used a 2.1–4.2 times longer training phase than other experiments, we examined whether elongating the training session changes the dynamic of the simulation (Fig. 1D). The simulation showed that the VDAC had already reached its asymptote during the initial phase of the training session (approximately 200 trials) and remained stable during the rest of the session. To conclude, all models acquired greater attentional allocation to the stimulus paired with higher EVs when the main manipulation was EV. These results are consistent with the core idea of VDAC. In all four studies, SPH-V and EH- α were always included in the top three best-fit models (Table 1, Fig. 2).

Training session

Next, we focused on the training session to understand the dynamics of the learning curves of two stimuli while pairing them with different types of rewards. In the previous section, we showed that a prolonged training session does not alter the asymptote or learning speed of VDAC. We selected another study for a detailed dissection of the training session. Anderson et al. (2011a) reported an RT of approximately 100 trial bins during a training session

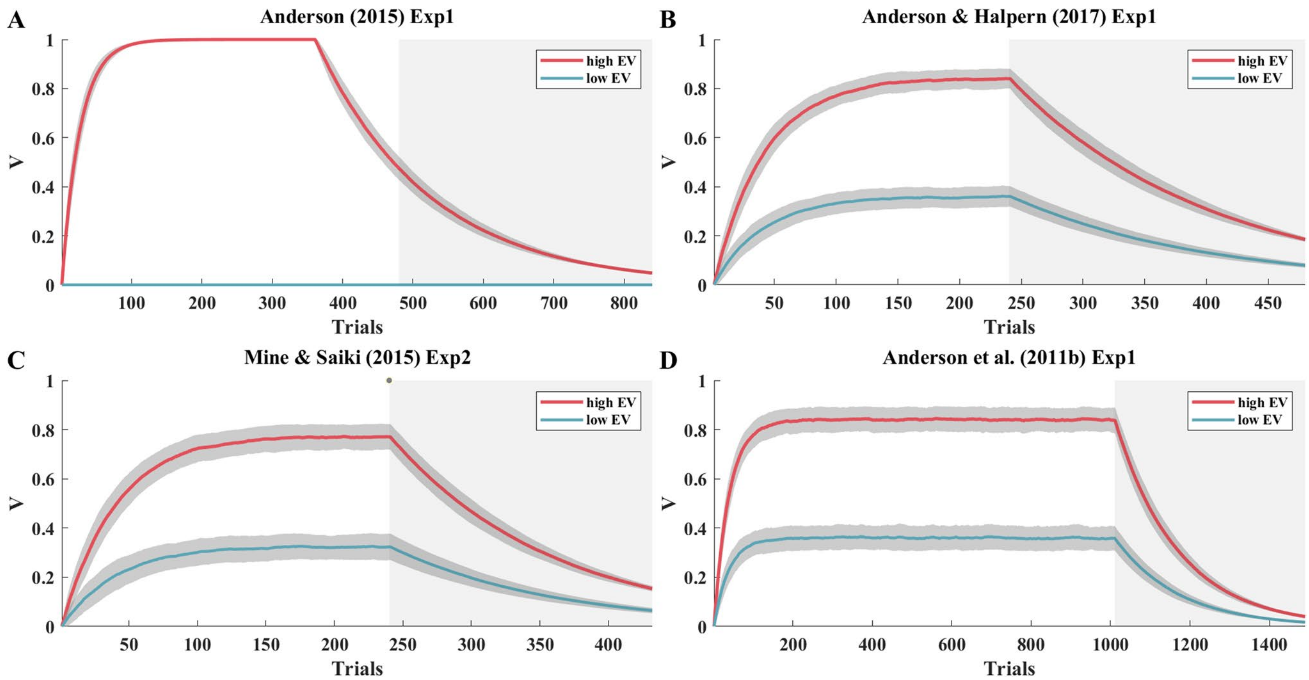

Fig. 1 Simulation results of RW-V model. The shades around the lines show a 1 standard deviation. The shaded areas indicate test sessions that the simulator targeted to fit

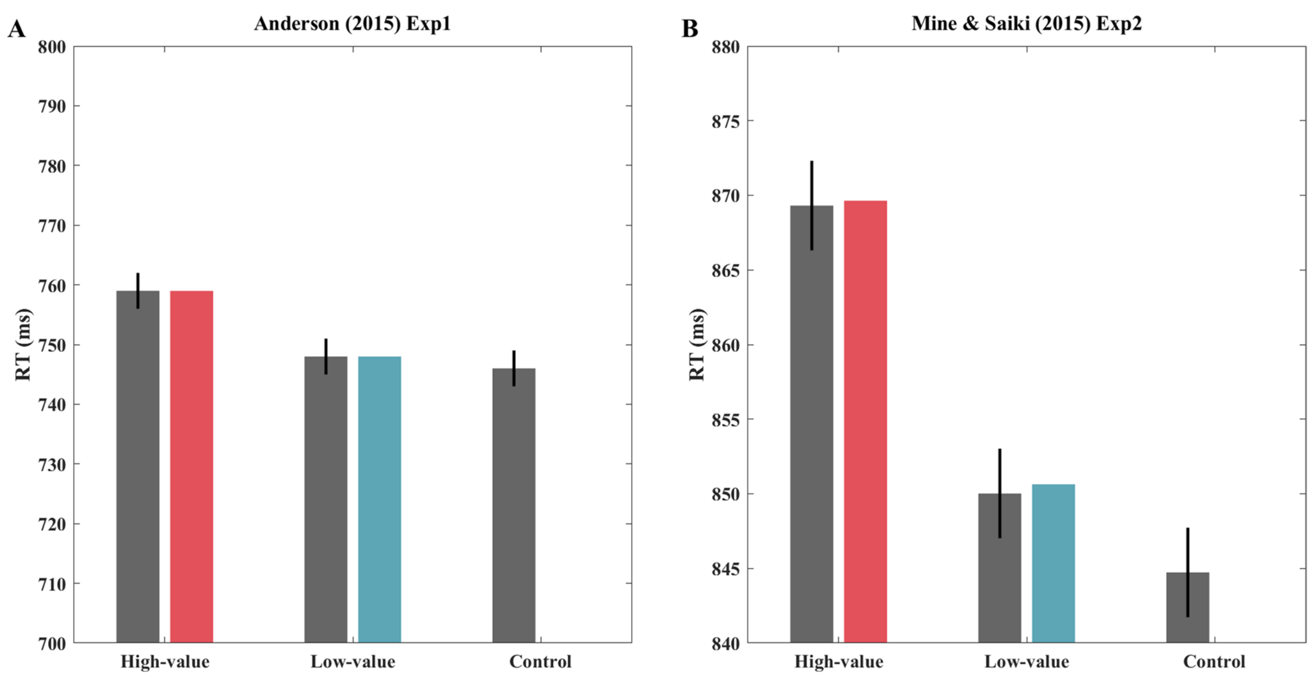

Fig. 2 Simulated behavior results using EH- α model (colors) along with the corresponding experiment data (gray) from two experiments: Anderson (2015) Exp1 (**A**) and Mine & Saiki (2015) Exp2 (**B**). Black lines represent the SEM. The SEM of simulated results are omitted due to the small size. The simulated reaction time (RT) for the former nontarget/control stimulus left empty, as models cannot predict control RT value, rather they calculate the difference of RT compared to the actual control RT value

Table 1 Model comparisons for expected value (EV) experiments

		Anderson et al.'s (2011b) Experiment 1		Anderson's (2015) Experiment 1		Mine & Saiki's (2015) Experiment 2		Anderson & Halpern's (2017) Experiment 1	
		BIC	Ratio with RW(α)	BIC	Ratio with RW(α)	BIC	Ratio with RW(α)	BIC	Ratio with RW(α)
V	RW	1.057E+06	0.947	1.144.E+06	0.806	7.829E+05	0.709	5.126E+05	0.850
	M	7.957E+05	**0.713**	7.762.E+05	**0.547**	3.470E+05	0.314	3.993E+05	0.662
	SPH	7.949E+05	**0.712**	7.849.E+05	**0.553**	3.162E+05	**0.287**	3.885E+05	**0.644**
	EH	1.066E+06	0.955	8.098.E+05	0.570	5.372E+05	0.487	4.569E+05	0.757
α	RW	1.116E+06	1.000	1.420.E+06	1.000	1.104E+06	1.000	6.034E+05	1.000
	M	1.086E+06	0.973	7.767.E+05	0.547	3.320E+05	0.301	3.993E+05	0.662
	SPH	7.986E+05	0.716	7.787.E+05	0.548	3.241E+05	**0.294**	3.910E+05	**0.648**
	EH	7.794E+05	**0.698**	7.749.E+05	**0.546**	3.228E+05	**0.292**	3.897E+05	**0.646**

Bold numbers indicate the best three simulation results

of 1,008 trials. We fitted each model to this training data to find the best parameter set that matches all 10 points of the learning curve. In all V models, the EV difference between the two stimuli resulted in a wide gap between the two acquisition curves from the beginning of the training phase (representative examples are shown in Figs. 3B and C; the SPH-V and EH-V models showed a similar result).

This phenomenon is not surprising in respect of associative learning models, as a stimulus paired with a larger reward is expected to develop higher attentional allocation

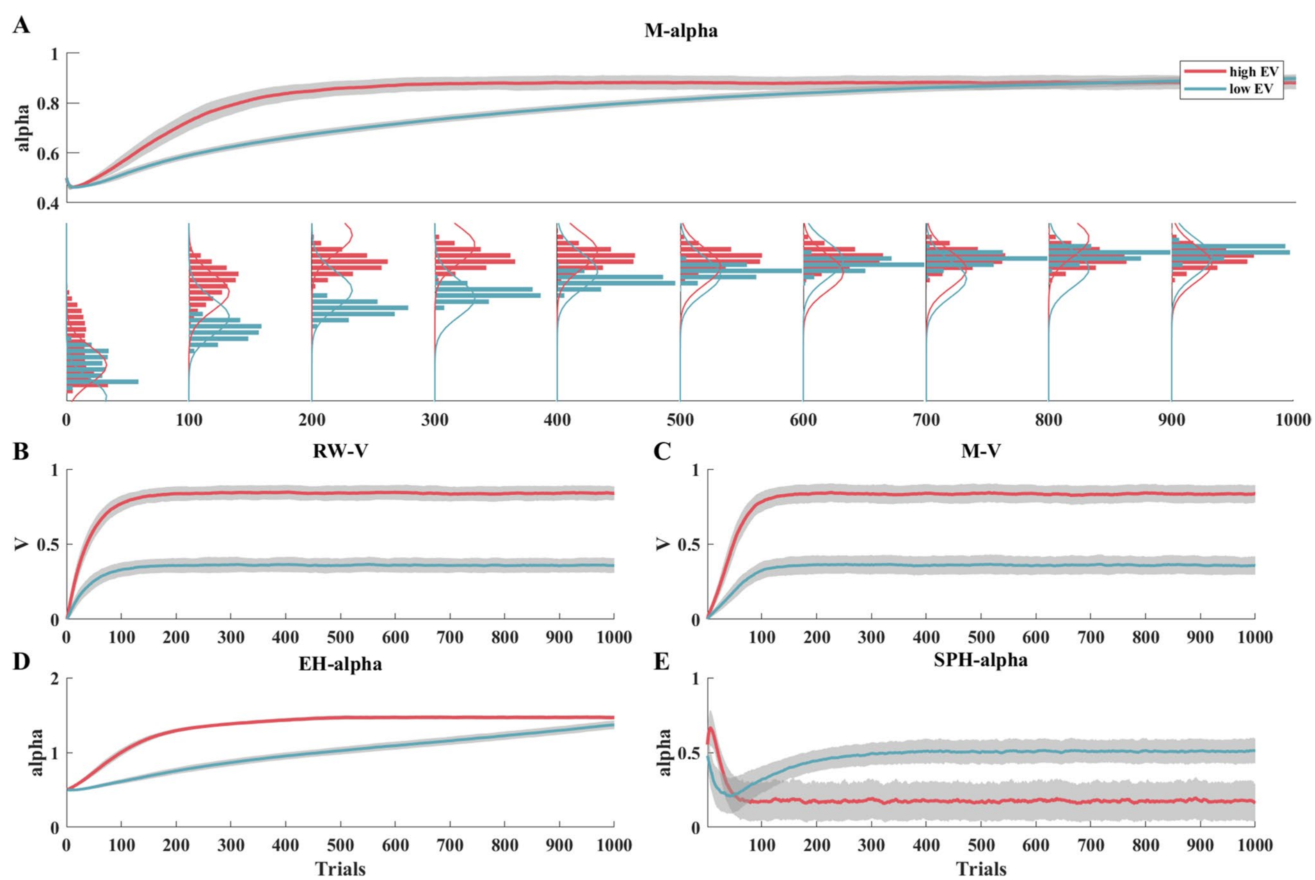

Fig. 3 Simulation results Anderson et al. (2011a) Experiment 1. Model parameters were fitted with ten block data from training session. M- α (**A**) and EH- α model (**D**) converges during the training, but asymptotes of the RW-V (**B**) and M-V (**C**) models exist apart from each other. The SPH- α model (**E**) failed to simulate the result. The shades around the lines show a 1 standard deviation

during the training session. However, a large body of studies, including that by Anderson et al. (2011a), reported a non-significant difference in behavior index between the two stimuli paired with different EVs. Although the similarities of the behavior during the training sessions are often interpreted as a ceiling or floor effect, two α models – the M-α and EH-α models – simulated this phenomenon by converging at the end of the training phase (Figs. 3A and D). Consequently, these two models had the lowest BIC ratio (Table 2). Interestingly, the acquisition curve of the M-α model was identical to that of the study, which had the largest gap during 200–300 trials and converged later in the session. In addition, the SPH- α model showed reversed attentional allocation to two stimuli (i.e., higher attentional allocation to the low reward stimulus), thereby failing to simulate behavior results in the experiment (Fig. 3E).

In summary, all V models and the two best-fit α models (M-α and EH-α) showed different predictions during the training session: the V models supports a higher VDAC effect on a high reward stimulus and the two α models expect no difference between stimuli. Regardless of whether the absence of behavior difference during the training session was due to a motor-cognitive limitation or not, this phenomenon may serve as a major limitation of V models.

Switching and inertia

Previous studies have confirmed that the effect of VDAC persists over a prolonged time, exceeding half a year (Anderson et al., 2011b; Anderson & Yantis, 2013). To test whether the associative learning models capture the stability of VDAC, we included a study that observed the inertia of VDAC (Liao & Anderson, 2020).

The most distinctive manipulation of this experiment involved switching the reward contingency of the two stimuli – old high-reward and new high-reward – from the third block of the experiment. Successful simulations demonstrated this switching by the intersection of the two curves of the old high-reward and new high-reward stimuli after the second training session (Fig. 4).

Although all simulations shared the same experimental schedule, how and when the two curves crossed varied across models. For example, in the case of the EH-V model (Fig. 4A), the extinction of the old high-reward stimulus and the acquisition of the new high-reward stimulus both induced the intersection in Block 3. In contrast, in other successful models, the crossing occurred solely because the newly associated stimulus outran the stable old high-reward value. Three models – RW-V, EH-V, and SPH-α – simulated the experimental result with the extinction of the old high-reward stimulus (Fig. 4A–C), and the other three models – M-V, SPH-V, and EH-α – did not exhibit extinction (Figs. 4D–F and 5). The M-α models could not reproduce the experimental results, as they predicted very little change in the α of all stimuli throughout blocks.

In the experiment, the old high-reward stimulus still drew attention to an extent comparable to the new high-reward stimulus after changing the reward condition. Moreover, in Block 4, the RT to the old high-reward stimulus was numerically faster than the low-reward stimulus, even though the old high-reward stimulus was not rewarded. In this regard, VDAC for the previous high-reward stimuli appears to resist extinction. The two best-fit models – the SPH-V and EH-α models (which have the two lowest BIC scores) – exhibited little or no extinction on the old high-reward stimulus (Table 3).

In conclusion, models that succeeded in simulating the switching experiment were divided into two types: (1) those in which switching occurs solely due to the acquisition of the new target, or (2) those in which switching occurs due to the combined effect of the acquisition of the new high-rewarded stimulus and the extinction of the previously

Table 2 Correlation of EV ratio and asymptote ratio of the simulation

		Anderson et al.'s (2011b) Experiment 1	Anderson & Halpern's (2017) Experiment 1	Mine & Saiki's (2015) Experiment 2	Anderson's (2015) Experiment 1
EV ratio		2.333	2.333	2.385	Inf*
V	RW	2.30	2.32	2.38	Inf**
	M	2.32	2.31	2.39	Inf**
	SPH	3.82	4.26	4.34	Inf**
	EH	2.30	2.87	2.90	Inf**
a	M	1.12	1.35	1.62	2.42
	SPH	1.50	1.97	1.90	Inf
	EH	1.78	1.52	1.53	3.23

*10 cents vs. 0 cent

**Zero associative strength to the non-rewarded stimulus

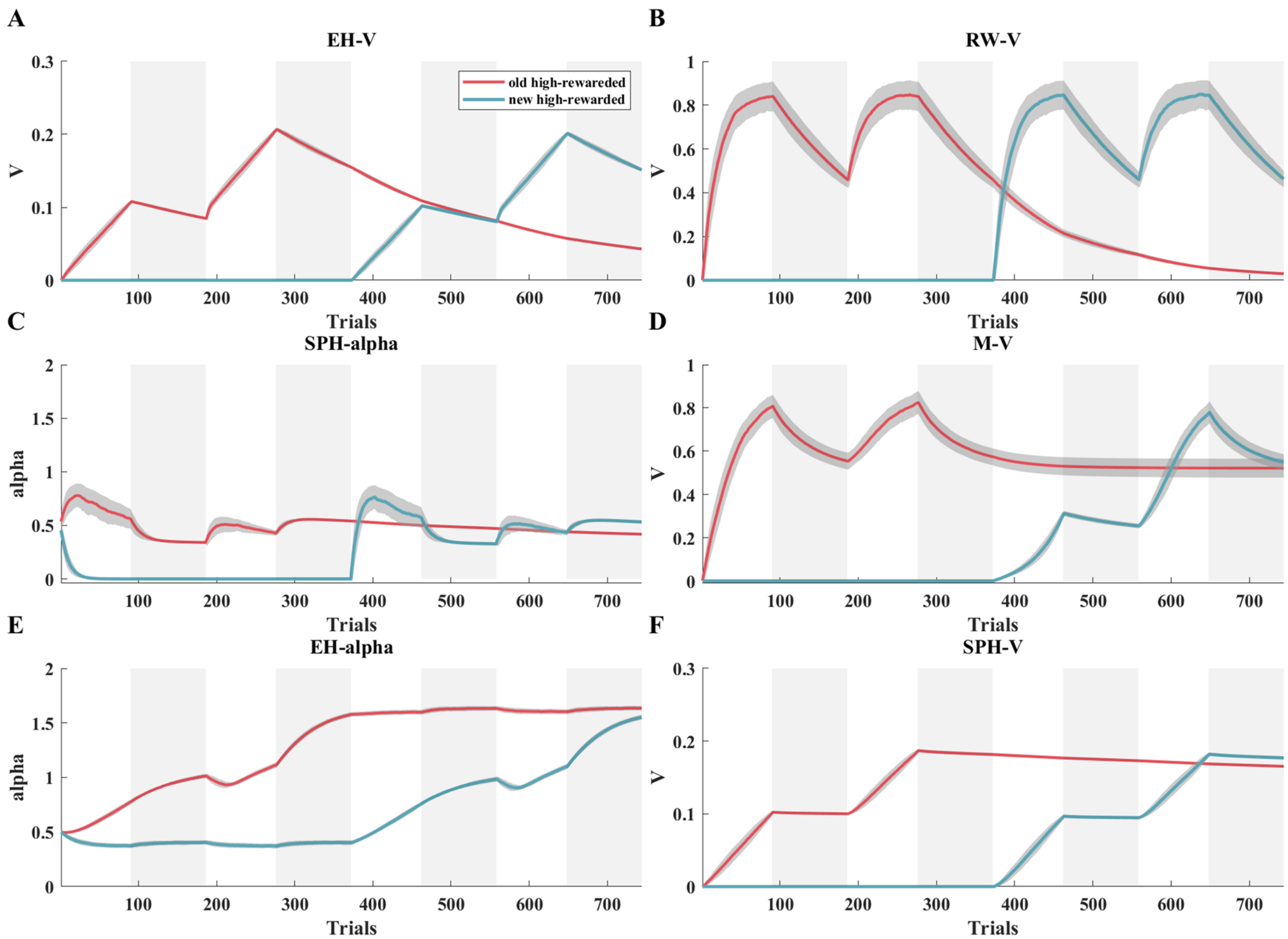

Fig. 4 Simulation results of Liao and Anderson (2020). The EH-V (**A**), RW-V (**B**) and SPH- α models (**C**) implement switching with both extinction of the old high-rewarded stimulus and acquisition of the new high-rewarded stimulus. However, in cases of the M-V (**D**), EH-α (**E**) and SPH-V (**F**) models, the acquisition is the main force driving the switching. The shades around the lines show a 1 standard deviation. The shaded areas indicate test sessions that the simulator targeted to fit. The legend applies to all the figures

rewarded stimulus. The quantitative comparison showed that high-performing models implemented the experiment result without extinction.

Uncertainty

Next, we included two studies that observed VDAC driven by uncertainty, not by EV. First, we fitted the model to the eye-movement data of two experiments conducted by Le Pelley et al. (2019). In the first experiment, two certain stimuli with EVs of 500 and 10 and one uncertain stimulus with an EV of 255 were used. Concurrent with the argument that the EV modulates the effect size of attentional bias, all models except one (the M-α model) showed a stimulus with the higher EV achieving a higher V or α value regardless of the uncertainty in the reward contingency (representative examples are provided in Figs. 6A and 7A; other models except the M-α model showed a similar result). In the case of the M-α model, the NP distractor's uncertain reward presentation decreased the α during the test phase, resulting in the worst fit (Figs. 6B and 7B). The NP distractor's decreased α value was below that of the low-reward distractor. This outcome is counterintuitive because the NP distractor has a higher EV value than the low reward distractor.

Next, we simulated the second experiment, which used the stimuli with the same EVs but a different level of uncertainty. Again, all models except the M-α model achieved a higher VDAC for the NP distractor. This result is consistent with the data obtained from the experiment (representative examples are provided in Figs. 6C, D, 7C, and D; all other models except the M-α showed a similar result). The failure of the M-α model in both experiments was induced by its expectation that more attention would be given to the predictable stimulus.

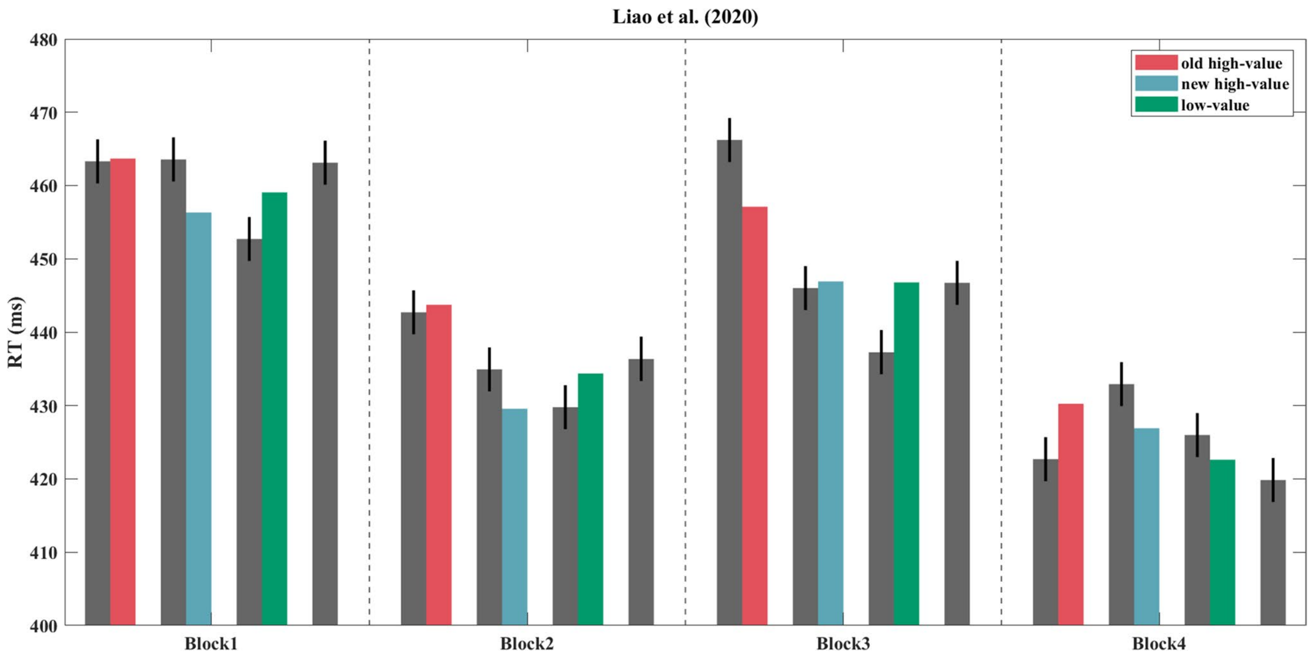

Fig. 5 Simulated behavior results using the EH- α model (colors) along with the corresponding experiment data (gray) during test sessions. Black lines represent the SEM. The SEM of simulated results are omitted due to the small size. The simulated reaction time (RT) for the former neutral stimulus left empty, as models cannot predict control RT value, rather they calculate the difference of RT compared to the actual control RT value

Next, we simulated the study by Cho and Cho (2021), in which reward magnitude and reward delivery probability were manipulated while maintaining the same EVs. The first experiment manipulated uncertainty by changing the reward probability. All simulations except the M-α model predicted a higher VDAC for the uncertainly rewarded stimulus in the first experiment (representative example are provided in Figs. 8A and 9A; other models except the M-α model showed a similar result). The differences between successful models were limited to the asymptote value during the training phase and the extinction speed in the test phase. Again, the M-α model failed to accurately anticipate and assign a larger α value to the certain stimulus (Figs. 8B and 9B) as in the experiments in Le Pelly et al. (2019).

The second experiment, in which the reward magnitude was altered to change the uncertainty, provided a similar simulation result, although the difference between the two stimuli was dampened during the second block of the test phase (representative examples are given in Figs. 8C and 9C; other models except the M-α model showed a similar result). Unsurprisingly, the M-α model failed again (Figs. 8D and 9D). Taken together, simulations of almost all associative learning models successfully predicted the magnitude of the uncertainty driven VDAC, even though the EV and the reward variance were fixed. However, the M-α model consistently failed to simulate the experiment in all studies in which EV was controlled.

Table 3 Model comparisons for Training and Switching experiments

		Anderson et al.'s (2011a) Experiment 1		Liao et al.'s (2020)	
		BIC	Ratio with RW(α)	BIC	Ratio with RW(α)
V	RW	3.047E+06	0.879	2.675E+06	0.998
	M	2.973E+06	0.858	2.351E+06	0.878
	SPH	2.267E+06	**0.654**	1.780E+06	**0.664**
	EH	2.383E+06	0.688	2.369E+06	0.884
α	RW	3.467E+06	1.000	2.679E+06	1.000
	M	2.006E+06	**0.579**	2.664E+06	0.994
	SPH	3.492E+06	1.007	1.956E+06	**0.730**
	EH	2.259E+06	**0.652**	1.794E+06	**0.670**

Bold numbers indicate the best three simulation results

Discussion

The present study adopted four mathematical implementations of associative learning models – RW, Mac, SPH, and EH models – to distinguish factors and explain the cognitive processes underlying VDAC. From each model, two output variables, V and α, were included in the model-fitting

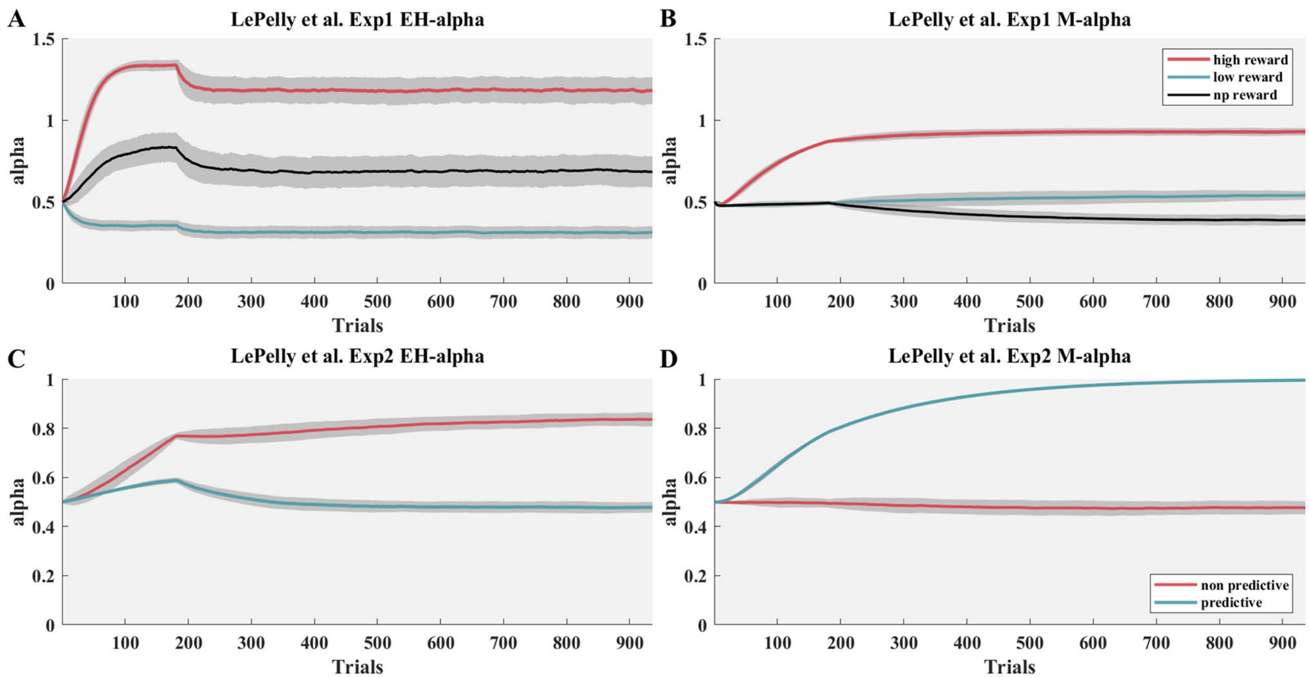

Fig. 6 Simulation results of two experiments from Le Pelley et al. (2019). The best fit model from each experiment (**A** and **C**) is plotted on the left, and the failed model (**B** and **D**) is located on the right. The shades around the lines show a 1 standard deviation. The shaded areas indicate test sessions that the simulator targeted to fit. The legend applies to figures from the same experiment

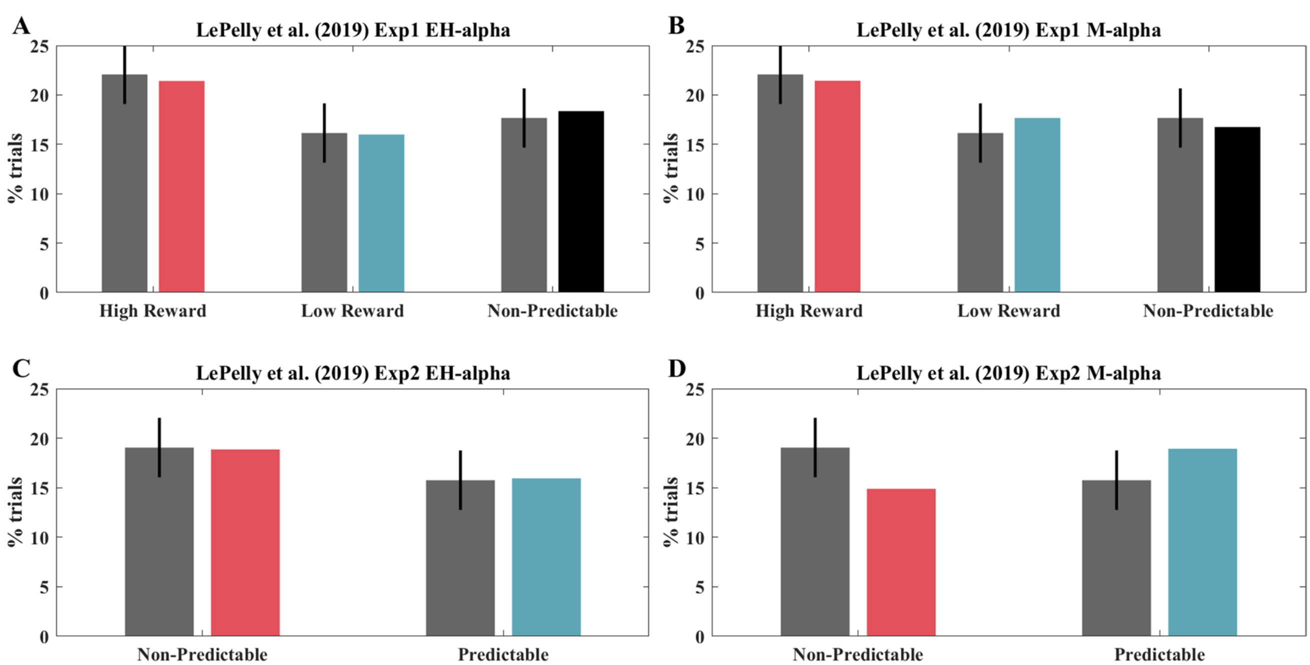

Fig. 7 Comparison between experiment data (gray) and corresponding simulated data (colors) from the best (left; **A** and **C**) and the worst (right; **B** and **D**) models. Black lines represent the SEM. The SEM of simulated results are omitted due to the small size

analysis, which yielded eight implementations in total (note that the RW- α model, which assumes equal attentional allocation to all stimuli, was used for the comparison purpose only). Although most models successfully predicted behavioral data from experiments, two models – the SPH-V and EH-α models – generally performed best across multiple

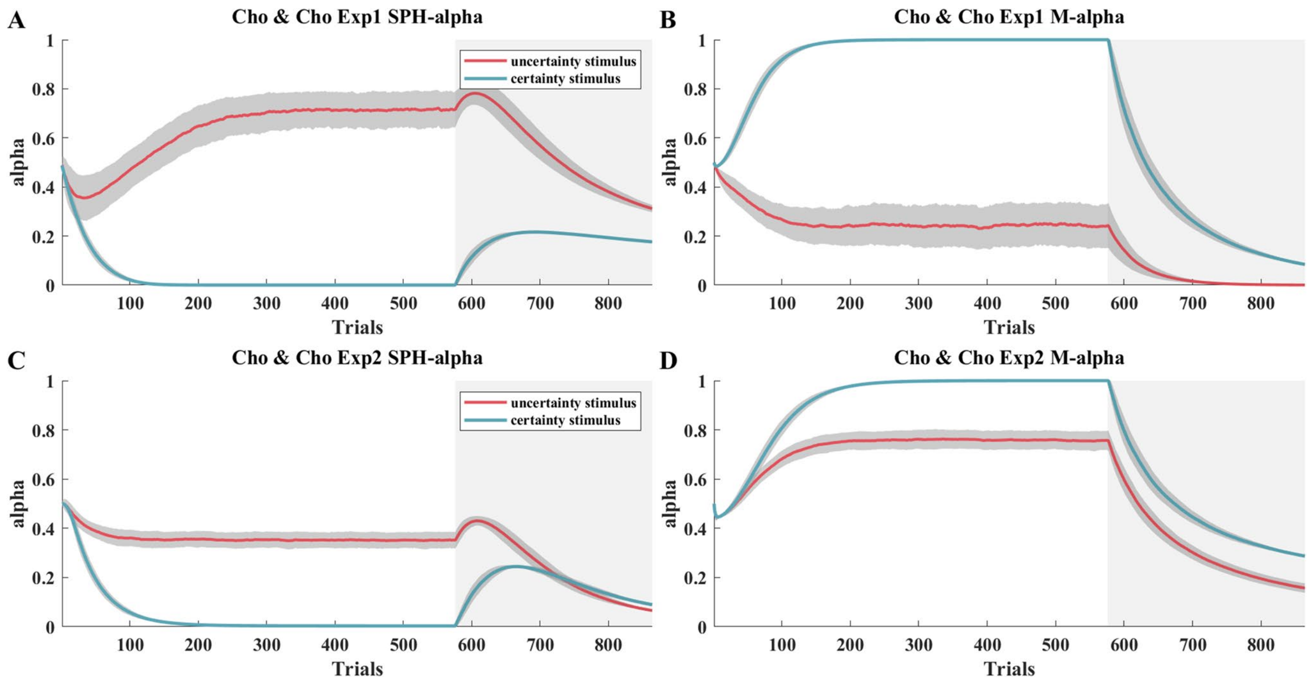

Fig. 8 Simulation results of two experiments from Cho and Cho (2021). The best fit model from each experiment (**A** and **C**) is plotted on the left, and the failed model (**B** and **D**) is located on the right. The shades around the lines show a 1 standard deviation. The shaded areas indicate test sessions that the simulator targeted to fit. The legend applies to figures from the same experiment

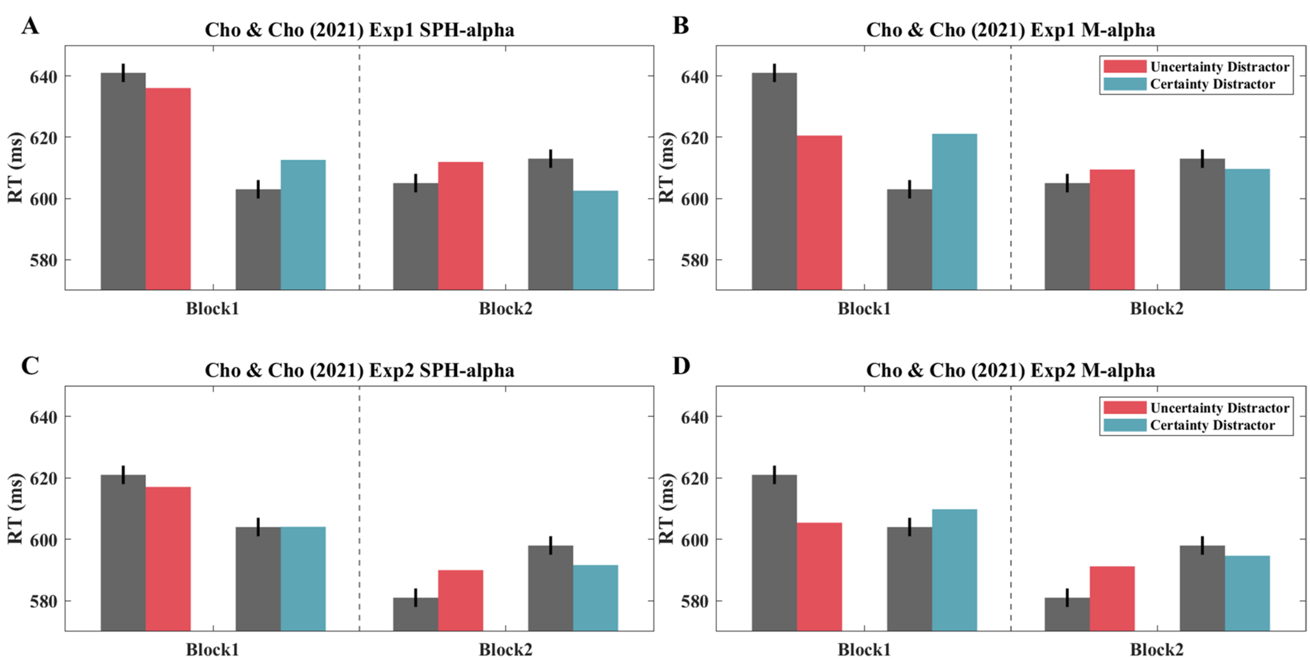

Fig. 9 Comparison between experiment data (gray) and corresponding simulated data (colors) from the best (left; **A** and **C**) and the worst (right; **B** and **D**) models. Black lines represent the SEM. The SEM of simulated results are omitted due to the small size

studies. Here, we discuss the performance of the learning models concerning the output values, V and α, and their predictions on the extinction phenomenon in the VDAC experiment scheme.

Associative strength (V) versus associability (α)

Many studies have attempted to incorporate associative learning theories to elucidate the mechanism behind VDAC (Anderson, 2015; Cho & Cho, 2021; Le Pelley et al., 2016; Le Pelley et al., 2015; Le Pelley et al., 2019; Watson et al., 2019). Le Pelley and his colleagues (2019) implemented the Mac model and used the α value to simulate the difference between the attentional capture of the predictive and nonpredictive stimuli. The α value has been used interchangeably with "attention" (Mackintosh, 1975) or has at least been described as a component reflecting attentional allocation (Esber & Haselgrove, 2011; Frey & Sears, 1978). In this regard, Le Pelley et al. (2019) interpreted α as the level of attention. When modeling the "value"-driven aspect of attention, however, the associative value, V, which is a direct measure of how much value the stimulus anticipates, appears to be a more reasonable element than α. In this vein, Le Pelley et al. (2015) proposed a more straightforward computational model for VDAC in which attention is a direct function of the learned value. To determine whether V models and α models predict different outcomes (and, if so, how they are different), we included two versions of each implementation of associative model and compared the goodness of fit.

When there was an evident EV difference between paired rewards, models utilizing the V value had a lower BIC than those that utilized α. Notably, the SPH-V model was on the list of best-fit models in all studies that manipulated the EV as the primary independent variable. Moreover, we observed a positive correlation between the EV ratio and the ratio of asymptote of the simulation (Table 2). The V model simulation results showed that a stimulus with a proportionally higher EV resulted in a more potent attentional capture during the training session than the other stimulus. This phenomenon was also observed by Le Pelley et al. (2019), who used three stimuli with different EVs (500 points, 255 points, and 10 points).

The simulation results of the V models, as well as the experiment result, demonstrated that the strength of attentional capture changed according to the stimuli's EV. The simulation revealed that relative differences (e.g., 100:1 = 100), rather than absolute differences (100-1 = 99), are critical in VDAC. This outcome is in line with general ideas in behavioral economics (the diminishing sensitivity principle; Kahneman & Tversky, 1979). Similarly, the importance of the relative difference in VDAC was directly demonstrated by Kim et al. (2022); for example, 100-valued stimuli captured more attention compared to 1-valued stimuli than 1,000-valued stimuli captured when compared to 901-valued stimuli.

Although models using V to measure attentional capture succeeded in simulating the effect of EV on VDAC, these models have several shortcomings. First, models based on the V always anticipate greater attentional allocation to the stimulus associated with a higher EV. The failure of the V models can be seen in the simulation of the first experiment by Le Pelley et al. (2019). In this experiment, three stimuli (high value, nonpredictive, and low value) were employed, and their EVs (500, 255, and 10) were spaced by an equal distance. Although the V models predicted an equal behavioral difference between each stimulus pair (high vs. nonpredictive and nonpredictive vs. low), the only differences observed were between the high stimulus and the rest of the stimuli. In contrast, the models using the α value did not exhibit a linear relationship between the asymptote and EV. Instead, they showed more dynamic changes during the training session and were affected by other factors such as predictiveness and uncertainty.

Second, V models always suffer extinction if the stimulus is consistently presented without a reward. Alongside acquisition with the reward, extinction takes part in the other half of the associative learning. In most experimental VDAC paradigms, the previously paired stimulus is presented as a distractor without reward. This is a typical extinction protocol in an associative learning experiment. If the strength of VDAC is calculated by the V, the repeated presentation of the distractor should lessen the interference effect as the trial progresses. However, as described in the next section, the VDAC effect appears to be resistant to extinction. In contrast, α models do not suffer rapid decay during a testing session. The increase in the α value during the training session remains relatively stable compared to the V value. Notably, the EH-α model – a hybrid model that reconciled the influence of predictiveness from the M model and uncertainty from the SPH model – exhibited the best fit in nearly all simulations reported in this paper.

Lastly, the V models cannot explain the absence of behavioral differences during a training session. Although all V models predict higher attentional allocation to the stimulus paired with a higher EV, behavioral differences, such as RT or accuracy during the training sessions, are usually not observed (Anderson, 2015; Anderson et al., 2011b, 2013; Anderson & Yantis, 2012). Such results are typically interpreted as a task difference (as the training session emphasizes, while the testing session focuses on speed) or a ceiling/floor effect of behavior.

However, some α models can anticipate the phenomenon during the training session without other justifications. In the simulation experiment of Anderson et al. (2011a), two α models, M-α and EH-α, converged during the training session. The main reason for this phenomenon is that the α value of the low reward target continued to increase during the whole training session. Two models, M and EH, share the same characteristic, in that predictability increases the α value. Since the reward contingency remained unchanged during training, the α value of the low reward target was able to reach a similar level as the high reward target. Taken together, while models that measure VDAC with the V value can directly highlight the influence of EV, α models – particularly the EH-α model – can predict additional aspects of VDAC without further justifications.

Extinction and inertia on value-driven attentional capture

The Mac and SPH models both postulate that the cue's salience is determined by its role as a *predictor* of its following consequences (e.g., reward). The EH model, however, disavows such an assumption and follows a proposal by Wagner (1978) that the decrement in a cue's salience would occur when the cue itself is predicted by an external event such as context or an experiment schedule (Esber & Haselgrove, 2011). As a result, the EH-α model demonstrates distinctive characteristics compared to the other models. Most notably, the EH-α model does not produce a rapid decrease in α by simply discontinuing the association between the cue and its consequences (e.g., reward). Since there is sufficient evidence that the acquired VDAC does not typically suffer a rapid extinction, even when the reward is no longer available, models without rapid extinction may conveniently provide compatible simulations. In fact, the simulated results from the EH-α model outperformed other models in most of the experiments with significantly lower BIC scores (see Tables 1, 3, 4, and 5).

Further, the lack of rapid extinction shown by several models is also in line with the VDAC literature. For instance, VDAC has been observed to persist for several days up to as much as 9 months after reward learning in the absence of additional reinforcement, and it resists extinction even over several hundred unrewarded trials (Anderson et al., 2011b;

Table 4 Model comparisons for uncertainty experiments

		Le Pelly et al.'s (2019) Experiment 1		Le Pelly et al.'s (2019) Experiment 2		Cho & Cho's (2021) Experiment 1		Cho & Cho's (2021) Experiment 2	
		BIC	Ratio with RW(α)	BIC	Ratio with RW(α)	BIC	Ratio with RW(α)	BIC	Ratio with RW(α)
V	RW	2.318E+06	**0.871**	1.590E+06	0.979	2.027E+06	0.701	1.616E+06	0.766
	M	2.321E+06	0.872	1.563E+06	**0.963**	2.193E+06	0.759	1.688E+06	0.800
	SPH	2.347E+06	0.882	1.582E+06	0.974	1.677E+06	**0.580**	1.334E+06	**0.632**
	EH	2.310E+06	**0.868**	1.581E+06	0.974	1.715E+06	**0.593**	1.263E+06	**0.599**
α	RW	2.662E+06	1.000	1.623E+06	1.000	2.890E+06	1.000	2.110E+06	1.000
	M	2.375E+06	0.892	2.120E+06	1.306	2.955E+06	1.022	1.815E+06	0.860
	SPH	2.496E+06	0.938	1.539E+06	**0.948**	1.460E+06	**0.505**	1.202E+06	**0.570**
	EH	2.311E+06	**0.868**	1.536E+06	**0.946**	2.121E+06	0.734	1.750E+06	0.830

Bold numbers indicate the best three simulation results

Table 5 Summary of best fit models (O: Best 3 models, X: worse than RW- α)

	RW-V	M-V	SPH-V	EH-V	M-α	SPH-α	EH-α
Anderson et al.'s (2011b) Experiment 1		O	O				O
Anderson's (2015) Experiment 1		O	O				O
Mine & Saiki's (2015) Experiment 2			O			O	O
Anderson & Halpern's (2017) Experiment 1			O			O	O
Anderson et al.'s (2011a) Experiment 1			O		O	X	O
Liao et al.'s (2020)			O			O	O
Le Pelly et al.'s (2019) Experiment 1	O			O			O
Le Pelly et al.'s (2019) Experiment 2		O			X	O	O
Cho & Cho's (2021) Experiment 1			O	O	X	O	
Cho & Cho's (2021) Experiment 2			O	O	X	O	

Anderson & Yantis, 2013; Della Libera & Chelazzi, 2009; Stankevich & Geng, 2014). Apart from the prediction based on classical conditioning, where a previously conditioned response to a reward-predictive stimulus is expected to vanish in the absence of reinforcement (Pavlov, 1927), most results in the VDAC literature report no significant reduction in impairment over the course of a test phase (Anderson et al., 2011b; Anderson & Yantis, 2012, 2013; Bucker et al., 2015; Failing & Theeuwes, 2014; Rothkirch et al., 2013; Sali et al., 2014; Stankevich & Geng, 2014; Theeuwes & Belopolsky, 2012).

These findings strongly indicate that reward learning forms an unusually persistent and highly extinction-resistant change in attentional priority that is biased in favor of previously reward-associated features even when they are no longer predictive of reward (Milner et al., 2023). Furthermore, the SPH-V model successfully simulated the inertia of VDAC observed by Liao and Anderson (2020) without rapid extinction, along with the EH-α model. As presented in the *Results* section, several models tried to simulate the exchange of VDAC using both the acquisition of the new high distractor and the extinction of the old high distractor. However, the two best models, SPH-V and EH-α, which simulated the result without the extinction, demonstrated that a sufficiently extended time (trials) was required to update or recalibrate previously acquired VDAC (Table 3). Collectively, two associative learning models, EH- α and SPH-V, account for the resistance to either the extinction or inertia of VDAC.

Associative learning characteristics in VDAC (modeling latent inhibition)

Most of the VDAC literature assumes that associative learning influences VDAC. However, as discussed, various characteristics, including resistance to extinction and the absence of behavioral differences during training, refute this notion. For the following reasons, further examination of the characteristics of VDAC must be conducted to conclude that VDAC is not a novel cognitive function but a variant or result of associative learning.

Latent inhibition is a phenomenon of associative learning whereby pre-exposure to a stimulus retards the subsequent association between the stimulus and the unconditioned stimulus (Lubow, 1973; Lubow & Moore, 1959). It presented a great challenge in developing associative learning models as it is one of the major failures of the RW model (Miller et al., 1995). RW model variants, including the Mac and PH models, overcame this shortcoming by adding a rule to change the α of a neutral stimulus. Although the two models implemented the change in α using different methods, both models can simulate this phenomenon.

Latent inhibition can serve as a good starting point for checking whether VDAC follows the basic phenomena of associative learning. First, regardless of the simulated outputs of V or α, all models except the RW model predicts lower attentional capture for a pre-exposed stimulus. Since V did not change during the pre-exposure session, all models emulated this phenomenon by lowering the α. Therefore, interpreting the experiment result is relatively easy, as this phenomenon does not tackle associative learning's mathematical implementation problems.

Second, it is possible to determine which output value of VDAC (V or α) can explain more about VDAC by looking at the temporal dynamics of the experiment result. As mentioned earlier, all associative learning models capable of describing latent inhibition used the change in the α during the pre-exposure session to account for the phenomenon. Therefore, if the α value is commensurate with VDAC, the behavioral difference will be observed from the beginning, even from the first trial. However, if VDAC is linked to V, a slower learning curve of attentional capture may emerge.

Third, this phenomenon is only driven by acquisition, thereby simplifying the application of associative learning to the VDAC effect. One of the unique characteristics that VDAC exhibits is resistance to extinction. Since latent inhibition can be observed during acquisition, it is possible to examine whether VDAC adheres to an associative learning scheme without addressing the extinction. Further human experiments observing latent inhibition can shed light on the underlying properties of VDAC and answer critical questions about the relationship with associative learning.

Conclusion

Associative learning encompasses multiple mathematical models that interpret the underlying processes of human cognition, and in turn, predict subsequent behaviors. Ample evidence suggests that associative learning accounts for various phenomena interpreted as VDAC. The present study formulated models and demonstrated that their predictions diverged when applied to various learning-related factors of VDAC other than the magnitude of reward. Importantly, the EH model, a hybrid model that supports a dual process of α modification, outperformed other models with regard to multiple factors. The high performance of the EH model demonstrates that complex models based on associative learning can more accurately explain the underlying mechanisms of human attention than other simple models.

However, while the EH model adequately explained various learning-related factors of VDAC, its performance was not stable across all studies considered here. We assume that cognitive factors other than associative learning also influence VDAC. Further research on how learning alters selective attention could further elucidate how perception and cognition modules interact to appropriately process and react to the environment.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.3758/s13423-023-02296-0.

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Data availability The data used in the simulation experiment are available at https://github.com/knowblesse/Modeling.

Code availability The code is available at https://github.com/knowblesse/Modeling.

Declarations

Conflicts of interest The authors declare no competing interests.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

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