

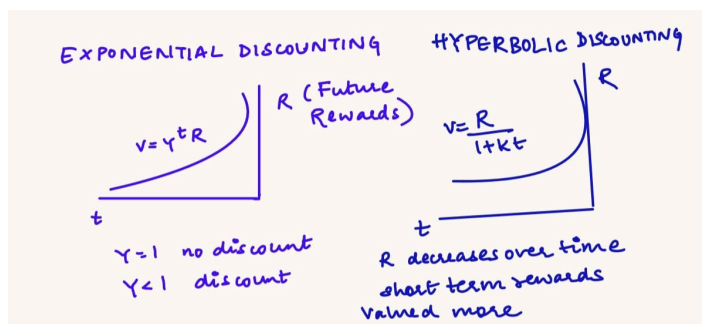
## Summary 5

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### Temporal Discounting

People's preferences generally remain stable when decision parameters are unchanged. However, in **intertemporal choices**, **time influences valuation through temporal discounting**, where distant rewards are perceived as less valuable. Given \$50 now vs. \$100 in 12 months, most choose the immediate reward, implying high discounting of future gains. However, for \$50 in 24 months vs. \$100 in 36 months, **people often pick the larger reward, showing reduced discounting** when both options are delayed.

This contradicts exponential discounting, where preferences should remain proportional over time, suggesting that **decision-making follows a hyperbolic** rather than strict exponential decay model.

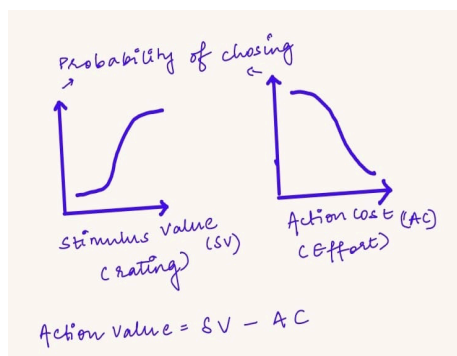


High discounters (high  $k$ ) prefer immediate rewards, while low discounters (low  $k$ ) wait for larger ones. A study of 20,000 participants found a 1000-fold variation in discount rates, influenced by genetics (12%) and environment (trust, scarcity, socioeconomic status).

### Neuroimaging during Discounting

Landmark studies show that while **individual neurons don't follow hyperbolic patterns**, behavior at the aggregate level does. A **mix of neurons** with different discounting profiles can collectively produce **hyperbolic discounting**.

### Action Value and Decision Making



**Stimulus value** is the perceived benefit or reward associated with an external option or cue. The **action cost** is the effort, energy, or risk needed to obtain the stimulus. If the action value is greater than 0 then we choose to act. Once values are computed, the brain implements choice through processes resembling **drift diffusion models (DDMs)**. Evidence accumulates over time until it reaches a decision threshold.

# Removing Confounders from Value Computation

To establish causal relationships in this decision-making framework, researchers must control for several potential confounds such as arousal and saliency, prediction error, timing effects, motion preparation etc.

## Value vs Saliency

**Saliency** is the **attention-grabbing quality of a stimulus**, independent of its value. It stems from features like brightness, contrast, or size. Emotionally charged, novel, or surprising stimuli are often more salient. High saliency can be mistaken for high value if not controlled for. To remove saliency we can

- Create stimulus sets where **value and saliency are uncorrelated**. Include all combinations of value and saliency
- Compare two **equally salient sets**
- Use **statistical models (GLM in fMRI)** to separate value and saliency.
- Have participants rate **value (preference) and saliency (noticeability) of stimuli**

## Value vs Prediction Error

Value signals (processed in **vmPFC**) and prediction error signals (processed in **ventral striatum**) occur in anatomically connected brain regions that form part of the same reward circuitry. Both signals can be triggered by the same stimuli. To remove prediction error we can

- Create distinct trial types like **GV (goal value) trials** which measure value without prediction error influence, **DV (decision value) trials** that capture decision value computation and **PE trials** which isolate prediction error signals
- Separate stimulus presentation (for value) from outcome delivery (for PE), using jittered delays to reduce signal overlap.
- Design conditions where value and prediction error are uncorrelated by **balancing prediction error** across different value levels.

## Value vs Action/Motor Preparation

To ensure that value computations are not confounded by motor or action preparation biases, we can do the following

- Introduce a **time delay** between the presentation of stimuli and the moment the subject is allowed to make a physical response
- Compare **responses across different motor outputs** (verbal, manual, eye movements) that theoretically have different motor costs. If value computations are truly independent, then the pattern of choices should be consistent regardless of which effector is used.
- In **electrophysiology**, use **separate regressors** for decision and motor preparation phases to isolate value-related brain activity.

## Gaze Fixation in Value Based Choices

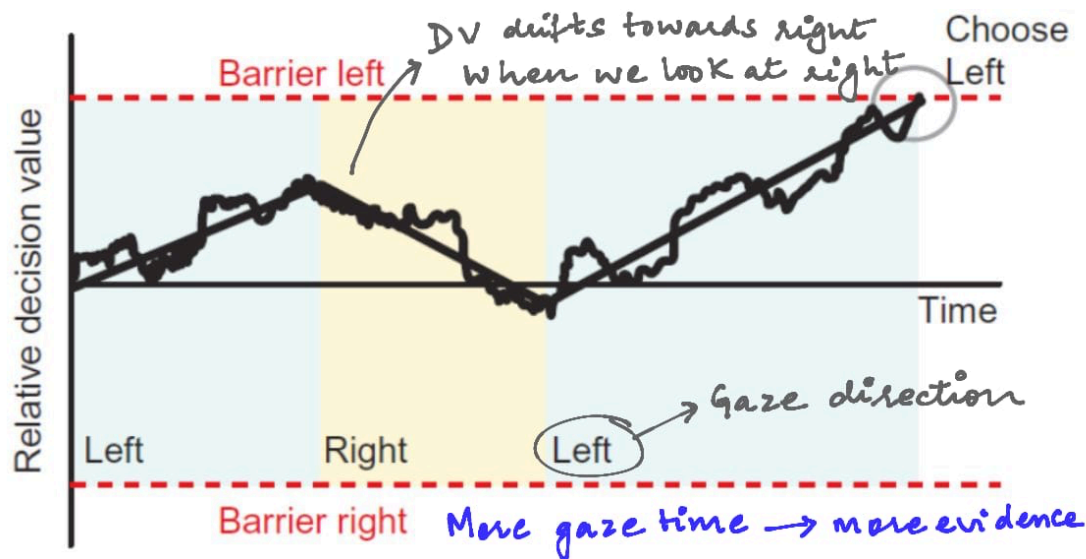
During decision-making, people often shift their gaze between options, suggesting saccades help compare or update values. Looking at an item can increase its perceived value or saliency. Eye movements and choices form a feedback loop, challenging the assumption that preferences are fixed from the start.

### Addressing Gaze Confounds

- Enforce [equal fixation times](#) for all options to prevent biased attention.
- [Randomize item positions](#) to avoid spatial biases influencing gaze patterns.
- Use eye-tracking data to [model how gaze modulates value signals over time](#).

## Attentional DDM (aDDM)

In DDM, one option is usually set as a reference, but real-world choices lack a fixed reference. Gaze shifts between options vary across and within trials, and since attention affects processing, [evidence accumulation depends on gaze](#) which is not captured by a DDM.



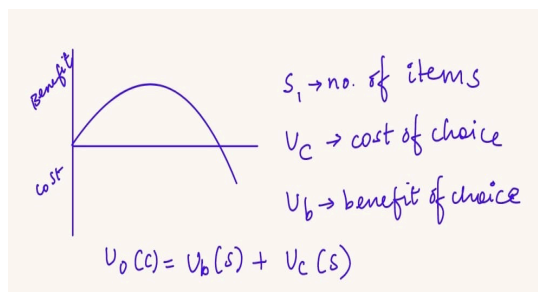
In this experiment design, participants begin with a [1000 ms enforced fixation](#) (e.g., on a blank screen or central point), followed by a free response phase where they can view two side-by-side options and decide at their own pace. A [1000 ms post-decision display or outcome follows](#). This setup allows researchers to track which item is fixated on first, the duration of gaze on each item, and whether early or late fixations predict the final choice. In aDDM, attention shapes decisions, [longer gaze increases evidence for that option](#), creating a feedback loop where [looking boosts preference, and preference drives more looking](#).

## Attention weighted value in vmPFC

vmPFC beta activity reflects the **value difference between options**. When fixating the **left item**, vmPFC activity **tracks (VL - VR) positively**. When fixating the **right item**, it tracks (VL - VR) **negatively**. vmPFC gives more weight to the item being attended, showing value representation is dynamic and attention-dependent.

## Paradox of Choice / Choice Overload

Having too many options can overwhelm people, leading to indecision or reduced satisfaction. Though large sets attract more interest, smaller sets often lead to more actual choices. Choice overload has pros like maximizing utility, enhancing freedom, and boosting motivation through variety, but also cons such as increased cognitive load, fear of regret, and decision paralysis.



Choice benefits follow an inverted U-shaped curve. Some variety increases value, but too many options cause overload and reduce satisfaction. The rising slope reflects limited choice, the peak is optimal variety, and the falling slope shows declining value from excess choice. However, real decisions can be more complex, with unpredictable or reversed preferences under high-choice conditions.

## Neural and Visual Signatures of Choice Overload

More options lead to more saccades, reflecting increased visual search. ACC activity, linked to conflict and cost-benefit analysis, follows an inverted U-shape increasing with choice set size, then declining. Eye movement areas show heightened activity, indicating greater cognitive effort. Together, ACC and eye data highlight the rising mental cost of too many choices.

## The Decoy Effect

The decoy effect occurs when **adding a third, less attractive option** subtly shifts preference between two original choices. The decoy is asymmetrically dominated clearly worse than the target but only slightly worse than the competitor making the target seem more appealing by comparison. This effect reveals how context and comparison can heavily influence decision-making. It challenges the idea that choices are always based on stable preferences. Marketers often use decoys to steer consumers toward more profitable options. It also highlights the importance of choice architecture in shaping behavior. Even seemingly irrelevant options can significantly alter final outcomes.

## Types of Decoys

### Similarity Effect (S)

A **new option is very similar to one of the existing choices**. This splits attention and preference, reducing the original option's popularity. Two chocolate bars are almost the same adding the second one makes people divide between them, lowering the first one's chance of being picked.

### Attraction Effect (D) ( Asymmetric Dominance)

A **clearly worse option is added** to make one existing option look better. The worse (decoy) option is similar to Option A but clearly inferior, making A look like the smarter choice. If popcorn A is ₹100, B is ₹150, and C (decoy) is ₹145 but smaller than B, C makes B look like a better deal.

### Compromise Effect (C)

A **very extreme option is added** to make one of the original options seem like a balanced "middle" choice. People tend to pick the middle ground. If small coffee is ₹100, medium ₹150, and now a jumbo for ₹250 is added, more people will pick the medium as a "reasonable" choice.

## Visual Attention in Decoy Decisions

When choosing among three items, spending more time looking at Option X leads to faster accumulation of evidence in its favor. If a **distractor decoy grabs attention**, it can shift gaze away from the main comparison between Options A and B. As we spend time examining the decoy and comparing it to its similar neighbor (e.g., Car A), that **neighbor may begin to seem more favorable once the decoy is mentally ruled out**. As a result, even though the decoy is technically irrelevant, its ability to draw attention can sway the final decision.

## Modeling the Decoy Effect - The Divisive Normalization Model

**Divisive normalization** explains how neurons adjust their responses based on the number and value of available stimuli. A **neuron's firing rate for a preferred option decreases** when more competing options are present, as **responses are divided by the total value in the scene**. This normalization helps explain why adding or removing items changes perceived value. It ensures **context-sensitive responses are stronger** when fewer items are present and weaker when there are many.

$$r_i = \frac{\text{drive}_i}{\alpha + \sum_j \text{drive}_j}$$

*stimulus drive for neuron i*

*constant*  $\alpha$  *sum across all relevant neurons in the population*