

# AI 507: Artificial Intelligence and Society



## #2 Learning

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# Flashlight

## Cognition

### History – fathers of cognitive science

Renée Descartes

Wilhelm Wundt

Alan Turing

John von Neumann

George Miller

Minds as  
computers

### Functional areas in the brain

Broca and Wernicke Areal

Functional areas

### Behaviourism: Stimulus → Response

Classical conditioning (Pawlow)

Reinforcement learning (Skinner)  
(operant conditioning)

### Stimulus → Organism → Response

## Core concepts

Sensory input

Mental representation

Cognitive architecture

Symbolic models  
(mind as computer)

Connectionist models  
(mind as deep network)

Deep encoding vs.  
superficial processing

## Intelligence

General intelligence “g”

IQ-tests

Justifications of discrimination

## Thinking

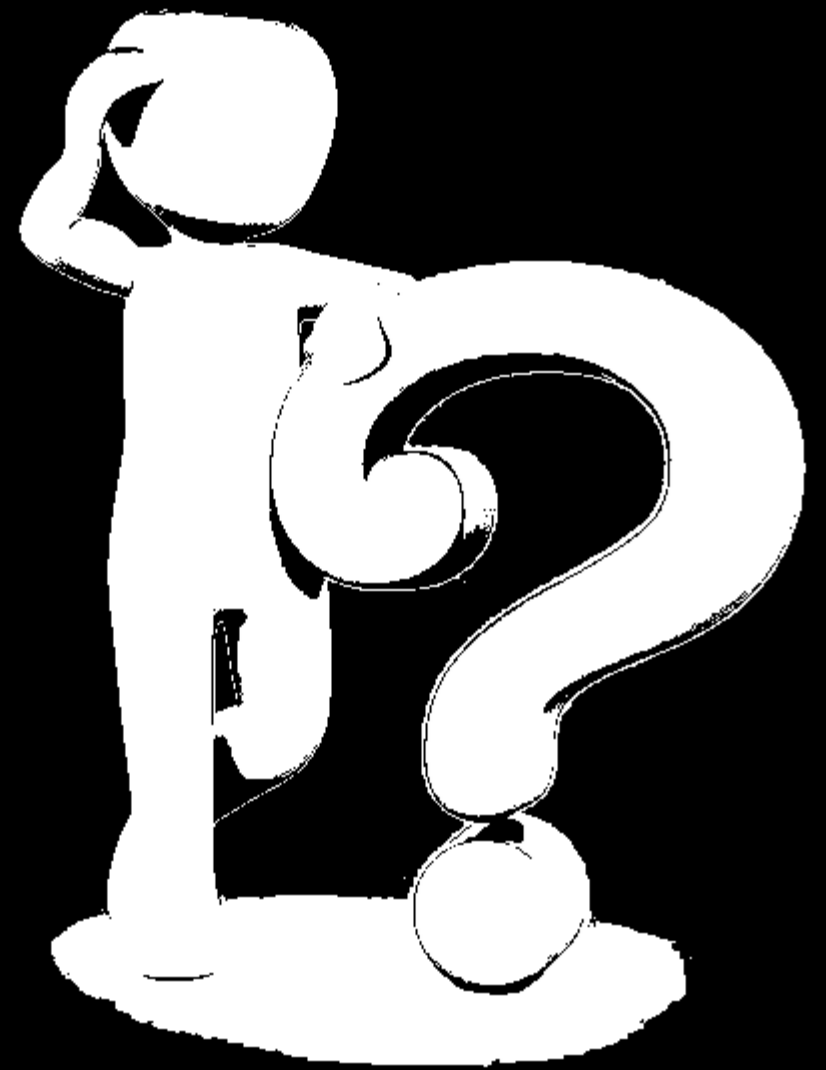
System I: Fast  
thinking

System II: elaboration



No elaboration without learning

**Any questions so far?**



# Then let's get started

At the end of today's lecture, you will...

- ...have an initial insight into human's memory works
- ...have a broad understanding of how humans learn
- ...have discussed how using LLMs can support but also impair your learning
- ...have discussed how we perceived the world (and how that relates to memory and learning)

**How do we remember?**

# Memory

(Miller, 1956; Neath & Suprenant, 2005)

- Three stages: Encoding, storage, retrieval
- **Encoding** = sensory processing (→ input)
- **Storage** =
  - **Short-term memory** (magic number “7” +/-2, today 4-5)
  - **Long-term memory**: *Explicit* (what happened when), *Implicit* (how)
- **Retrieval** (recognition, recall, reconstruction)
- Centrally: Encoding is directly linked to retrieval!
- Cues trigger retrieval
  - Strong cues → elicit a specific reaction *most* of the time
  - Weak cues → elicit a specific reaction *some* of time of among *some* people

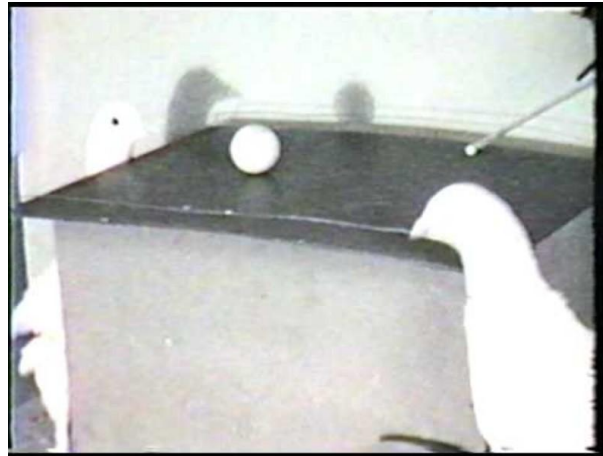


# Remember behaviourism?

## Classical conditioning



## Operational conditioning



- Initial learning works fastest with strong cues (constant reinforcement)
- However: learning is most stable when there are sometimes sanctions – the memory of what could happen does the job

# The role of schemes

(Bartlett, 1932)

- We store complex information in categorical rules or scripts
- Bartlett's *Scheme theory*: An active organisation of past reactions and experiences – regular behaviour is possible because we have serially organised past experiences as a unitary mass (Bartlett, 1932, p.201)
- For example, we have schema of “going to university”, “biking”, “driving a car” etc.
- Schemes combine knowledge about “what” and “how”
- We can recall and retell stories, change the details but keep the basic meaning – and both we and our audience will recall them

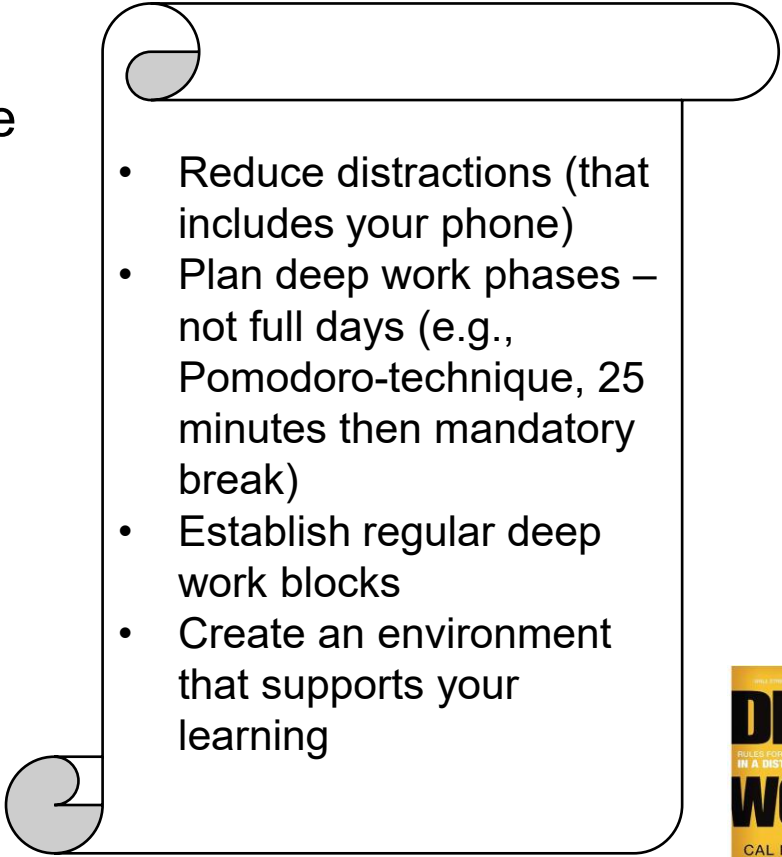


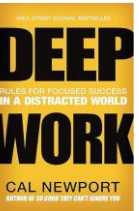
February 1948 photograph of Sir Frederic Bartlett. National Portrait Gallery via Wikipedia



# Practical consequences: Exam preparation

- Our working memory is quite limited – if we do too much things at the same time, no capacity is left
- Our brain does constantly process the environment in which we are in (even if not always attentively)
- These cues can make it easier to retrieve relevant memories (preparing not only the content but also the format of an exam)
- They can also make it harder (music with lyrics while reading, annoying room mates)
- Deep work and elaboration beats constant shallow work with distraction
- Reward yourself – but not all the time
- University as “test field” to develop schemata for teamwork, presentations etc.

- 
- Reduce distractions (that includes your phone)
  - Plan deep work phases – not full days (e.g., Pomodoro-technique, 25 minutes then mandatory break)
  - Establish regular deep work blocks
  - Create an environment that supports your learning



**What are your questions  
so far?**



# More generally: How do humans learn?

“We are not individually much cleverer than the average animal, a heron or a mole, but the knack of our species lies in our capacity to transmit our accumulated knowledge down to generations.

The slowest among us can, in a few hours, pick up ideas that it took a few rare geniuses a lifetime to acquire.”

(de Botton, 2019, p.1)

# How do we learn?

(Mikolov et al., 2013; Young & Wassermann, 2005)

## 1. Temporal contiguity (closeness in time)

- When two brain processes are activated together or in immediate succession, the activation of one spreads to the other (*Priming*)
- That's what we've seen in classic conditioning
- Word embeddings such as Word2Vec harvest the co-occurrence of events, in this case, words
- But attention:
  - Reinforcement learning (i.e., the consequence of a behaviour or stimulus) seems to be more powerful → Just watching soccer doesn't make you a successful player
  - The interval between the stimuli matters – and variety keeps your brain from zooming out (#Boring)

# How do we learn?

(Young & Wassermann, 2005)

## 2. Competition among predictors

- Our world is complex – in each moment, myriads of stimuli could be relevant
- To save energy, our brain thus sets them in direct competition to each other – only the best ones survive
- If there is already a relevant stimulus, new ones are blocked
- Only stimuli that provide unique new information are learned

=> our brains version of a step-wise regression



# How do we learn?

(Young & Wassermann, 2005)

## 3. Configural learning

- Our brain loves efficiency – so we often learn things as a “bundle” (→ Schema theory)
- Consider learning how someone looks like – for example Zendaya – you don’t learn her hair and eye colour separately
- That allows you to recognize her even with her “dune” eyes
- Generally, more complicated
  - Especially if there are a lot of irrelevant cues (→ working memory capacity)
  - Or if the cues are hard to distinguish (pink or red socks/ socks versus shoes)



<https://variety.com/t/zendaya/>



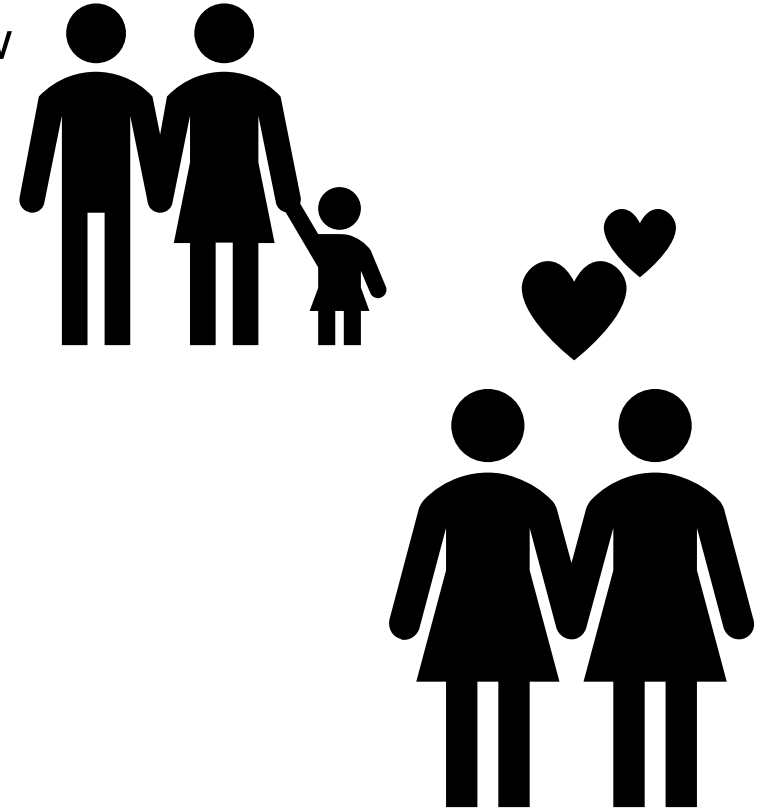
<https://movieweb.com/dune-2-zendaya-lead/>

# How do we learn?

(Shepart, 1987; Young & Wassermann, 2005)

## 4. Generalization and similarity

- Humans are extremely good in projecting our knowledge to new situation
- The higher the similarity between situations, the better
- Similarity = distance between representations (! Not situations but how we process and interpret them!)
- The lower the similarity between situations or stimuli, the better do we learn to distinguish between them
  - Shift your attention to different dimension
  - Shift your attention to different values on the dimension
- Captchas are used to train increasingly blurred images to train models in these difference





# Remember Schemata?

**Learning during human development = improvement of schemata**

- New information is added or assimilated to our current schemata
- If the information does not fit → unpleasant state might lead to schema change

**Schemata accelerate your learning!**

- Activate your knowledge and schemata to connect them with new information
- Use analogies & comparisons to harvest your schemata – and think about differences to make them more precise



[Jean Piaget in Ann Arbor \(cropped\).png](#) Unidentified (Ensign published by University of Michigan) via Wikipedia

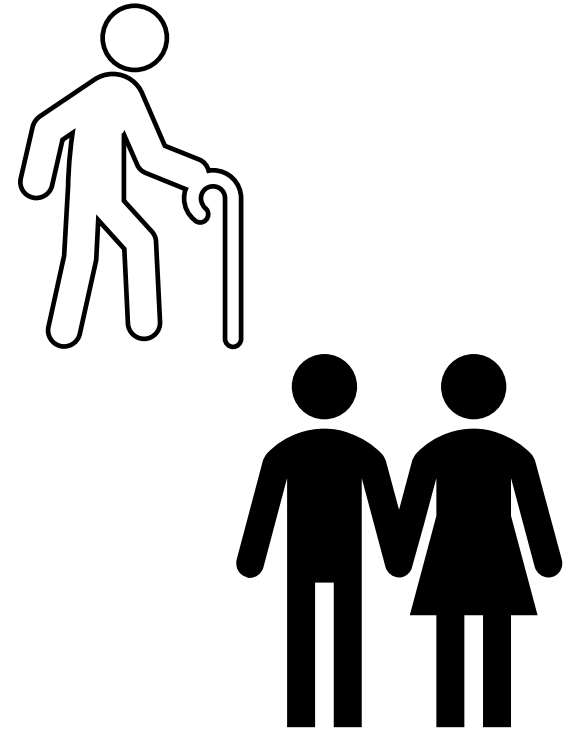


# How do we learn?

(Erdelyi, 2008; Young & Wassermann, 2005)

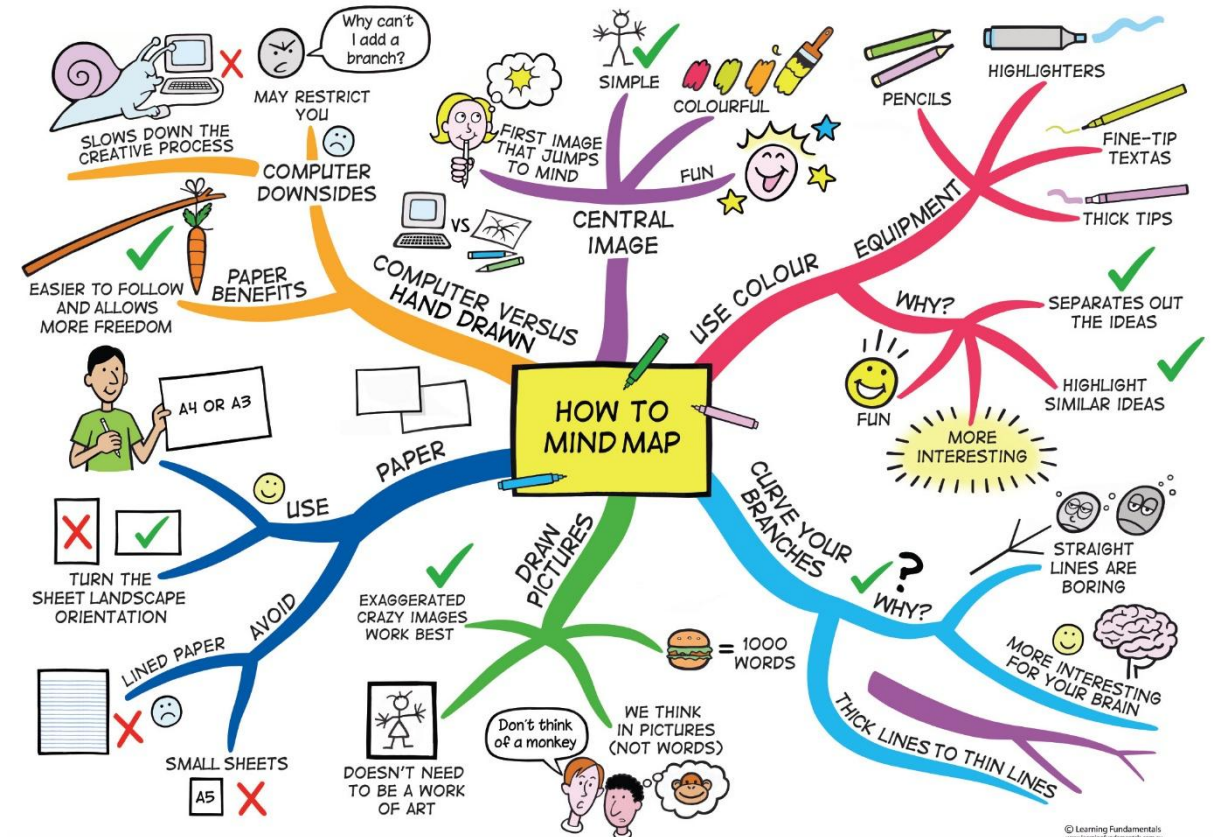
## 5. Unlearning

- If a stimulus is paired with a response and the response never comes, the pairing goes extinct over time
- However: If the stimulus + response is repeated, the pairing is there immediately and even stronger
- So, do we ever forget?
  - Information that is not encoded in short-term memory might indeed not be available any more → Central role of interference and working memory capacity
  - Information that has been encoded in the long-term memory is often rather not accessible but can be reconstructed (attention: error prone!)



# Practical consequences: Exam preparation

- Learning things together and relating them to each other
- But do not bore yourself – repetition alone is not attractive for the brain (try another modality to keep it interesting)
- Organise your knowledge – create patterns and schemes
- If you encode it carefully – you have good chances of finding it again, when you need it
- Mindmaps are really great

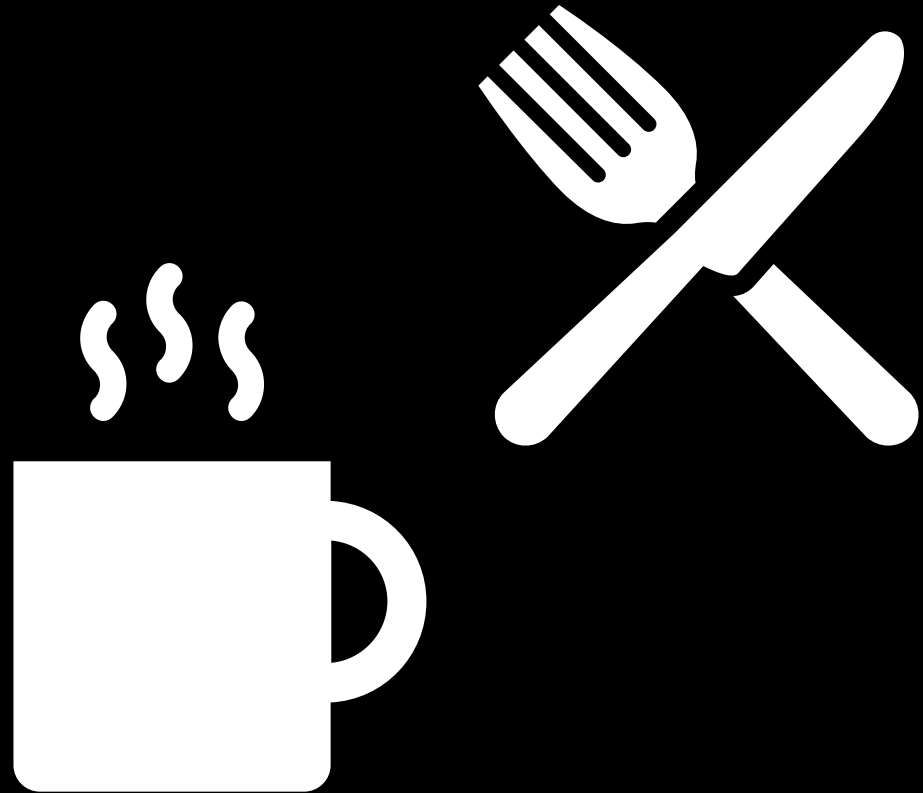


<https://learningfundamentals.com.au/resources/>

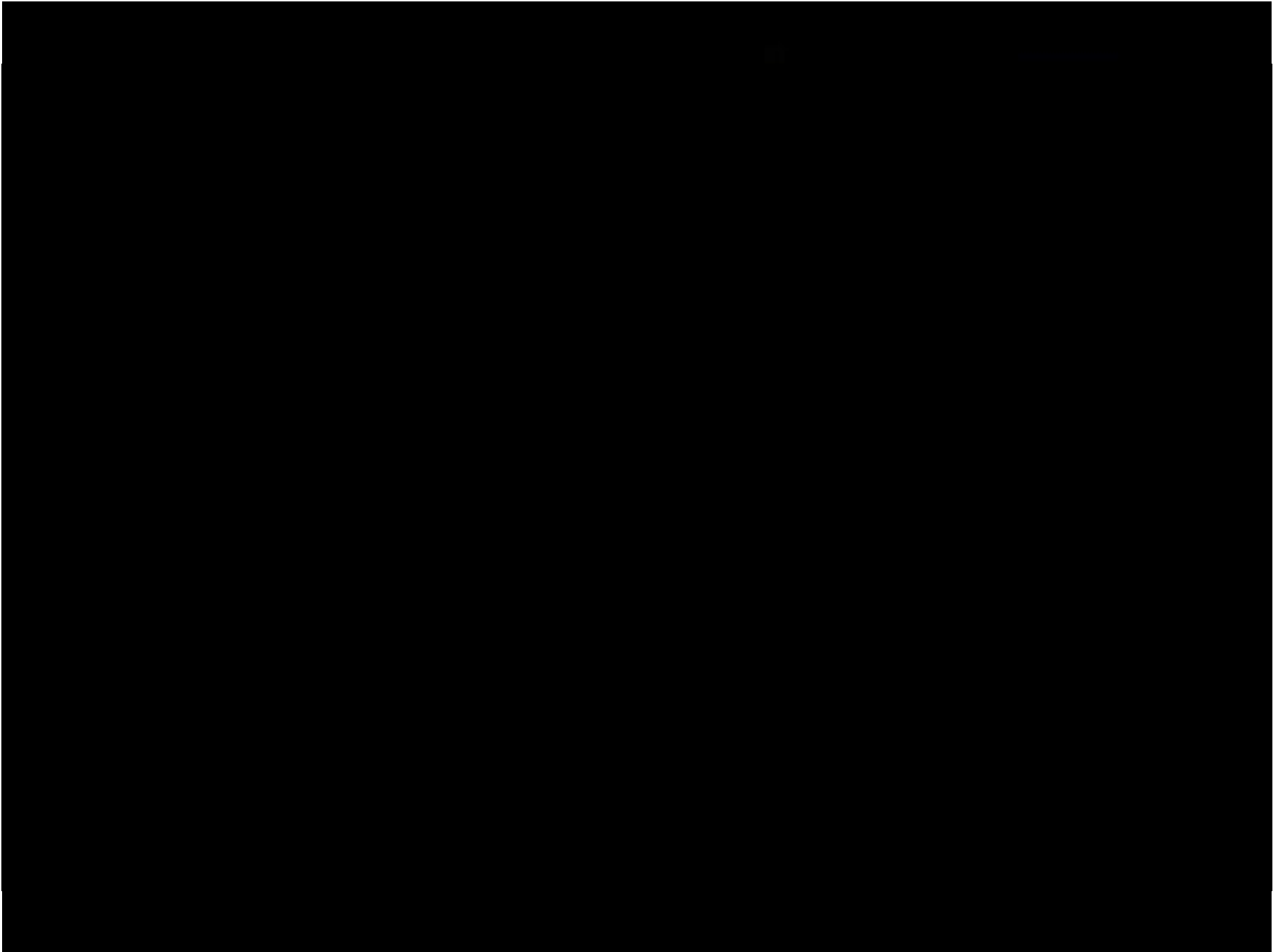
**What are your questions  
so far?**



**Time for a break**



**All learning starts with perception  
and awareness – so let's test  
yours!**

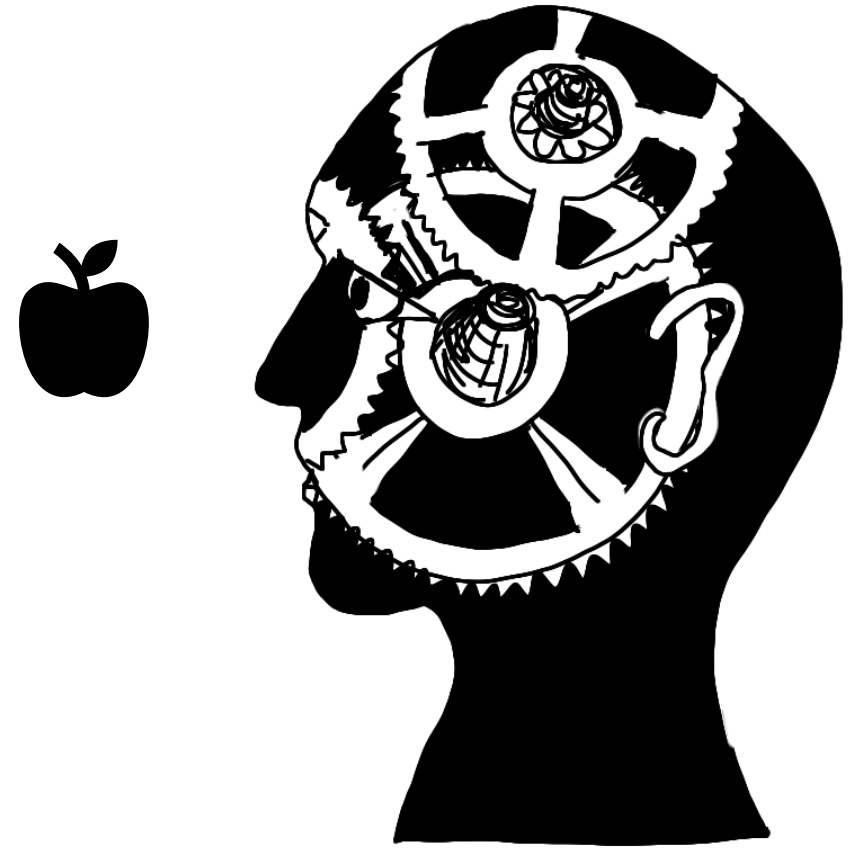


<https://www.youtube.com/watch?v=z-Dg-06nrmc&t=2s>

# How do we see ?

(Barry, 2020)

- Our eyes are a direct extension of our brain to the environment
- They send more data more quickly to our nervous system than any other sense
- But: We can also sense the environment without the eyes – and some extraordinary people have learned to use other senses to replace theirs
- But for today: Let's see how visual perception works in average-sighted people works



# Vision is complex

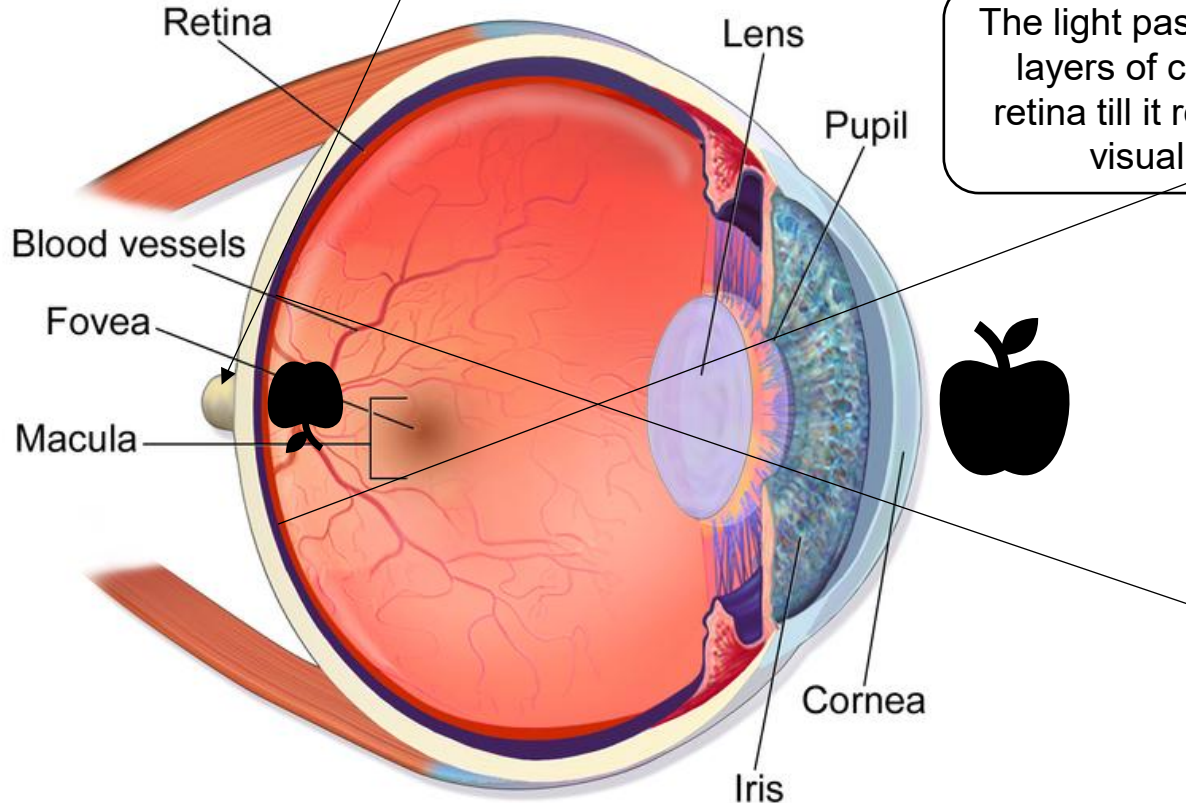
(Pinel, 2011; Nixon & Aguado, 2019)

Start of the optic nerve – “blind spot” :  
The brain “fills in” what’s missing!  
Perception is always also construction

Light enters through the  
pupil

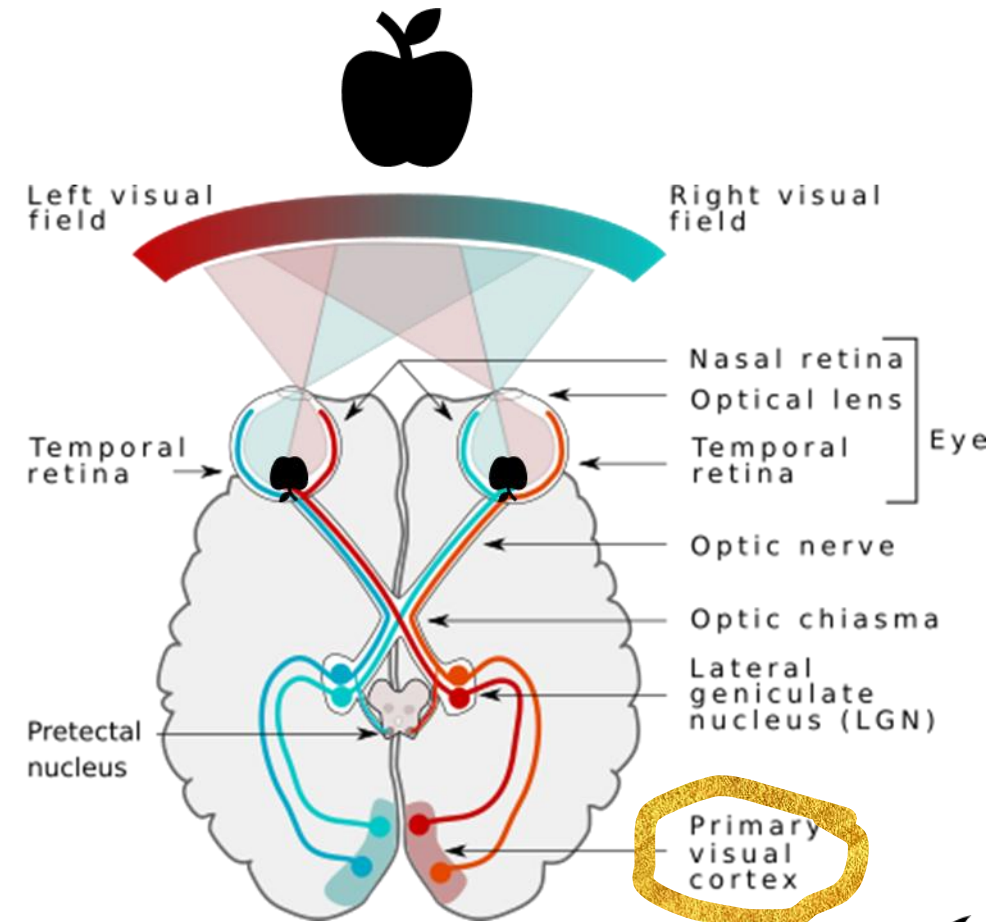
The pupil focuses the  
light onto the retina

The light passes several  
layers of cells in the  
retina till it reaches the  
visual cells



Eye Anatomy

Blausen, 2014



<https://commons.wikimedia.org/wiki/user:Perelloniето>





# Viewing is an interplay of functional systems

(Nixon, 2019; Pinel, 2011)

- Different neurons in the brain fulfil different functions
- Some are specialised in detecting movement
- Others focus on detecting colours, fine-grained structures and slow or fixed objects
- Our neurons are also specifically adapted to detect borders – they have developed complex mechanisms to enable us to navigate our environments!
- In the visual cortex, the input from different areas of the retina is processed, organised and aggregated
- The whole is more than the sum of its parts!
- Our brain can even implement missing parts – although the implementation might not always be correct – attention, memory, schemes drive what we see

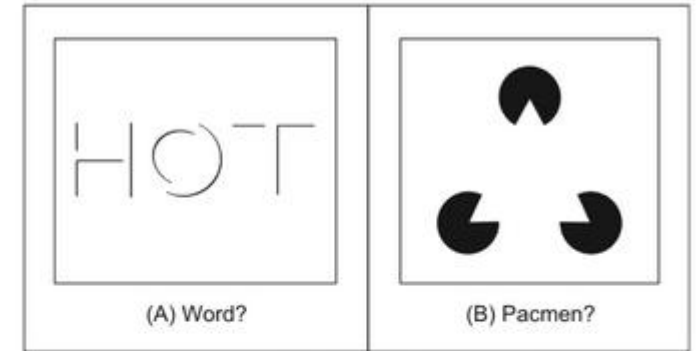


FIGURE 1.6 How human vision uses edges.

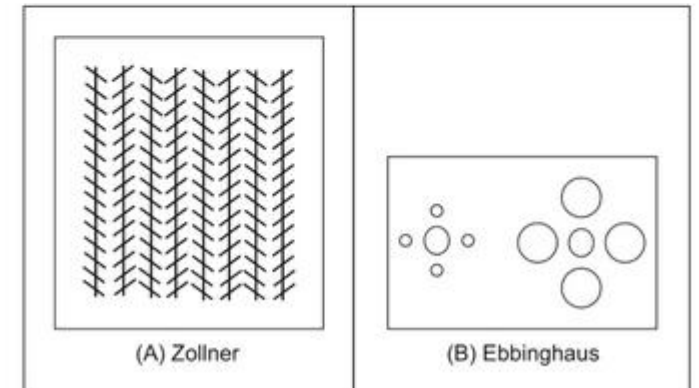


FIGURE 1.7 Static illusions.

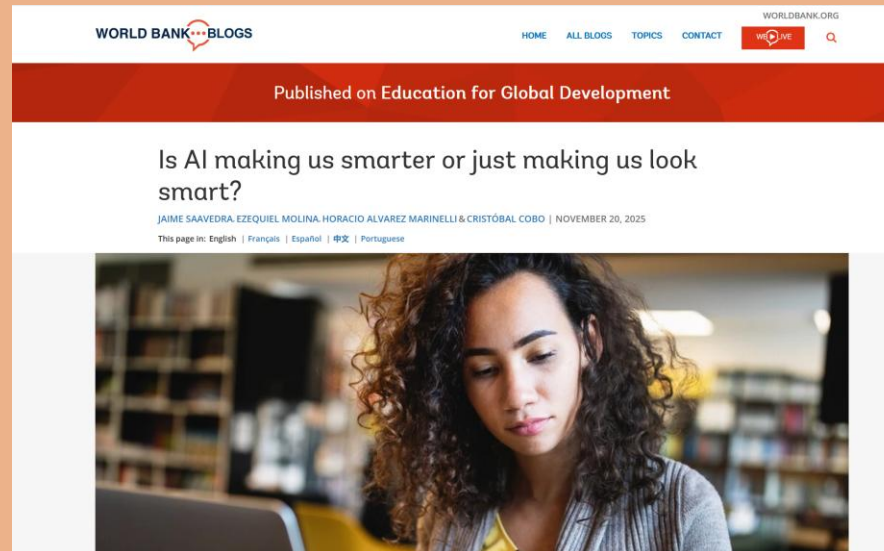
# The power of attention



# How does AI affect perception, memory and learning?

**6.5  
Billionen  
USD**

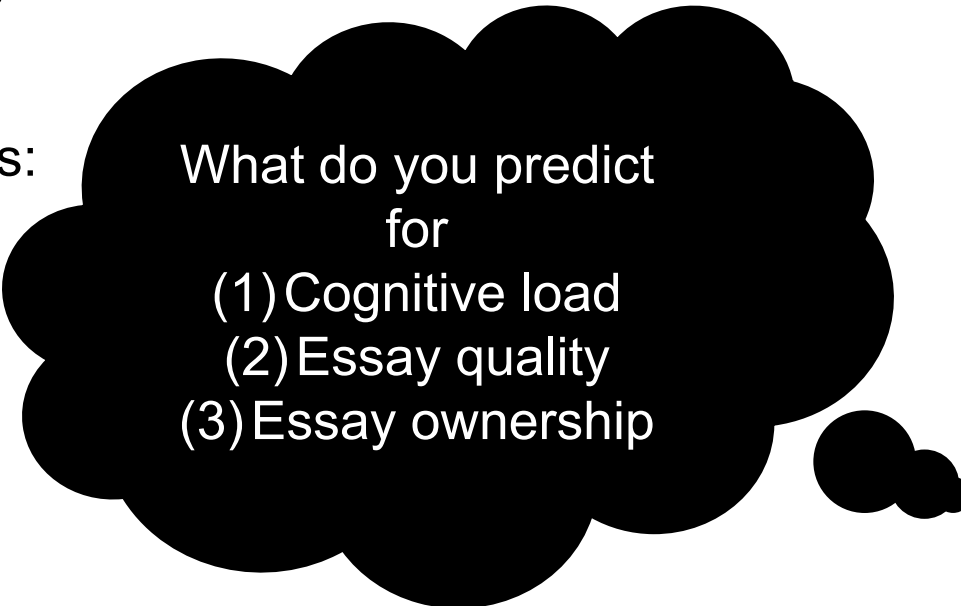
Estimated market size for AI in education



# Does AI make us smarter?

(Pearson, 2025; Kosmyna et al., 2025)

- Studies show that people who use technology for specific tasks (e.g., driving assistants) memorize these tasks worse (e.g., the way) – same goes for phone numbers
- Experiment with 54 participants that took part in three sessions: Brain-only, LLM, search engine
- Task was to write essays
- Measured cognitive load (via EEG), essay quality and how much participants felt that they “own” the essay
- Using LLMs reduced cognitive load – but also ownership and essay quality – especially over time more copy-and-paste and less memory of what one has actually written
- Attention: Small sample, normative implications unclear (do we \*need\* to know what we write) – but demonstrates that having LLMs learn for you does not work



What do you predict  
for  
(1) Cognitive load  
(2) Essay quality  
(3) Essay ownership

# The problem did not start with AI (Ward, 2021)

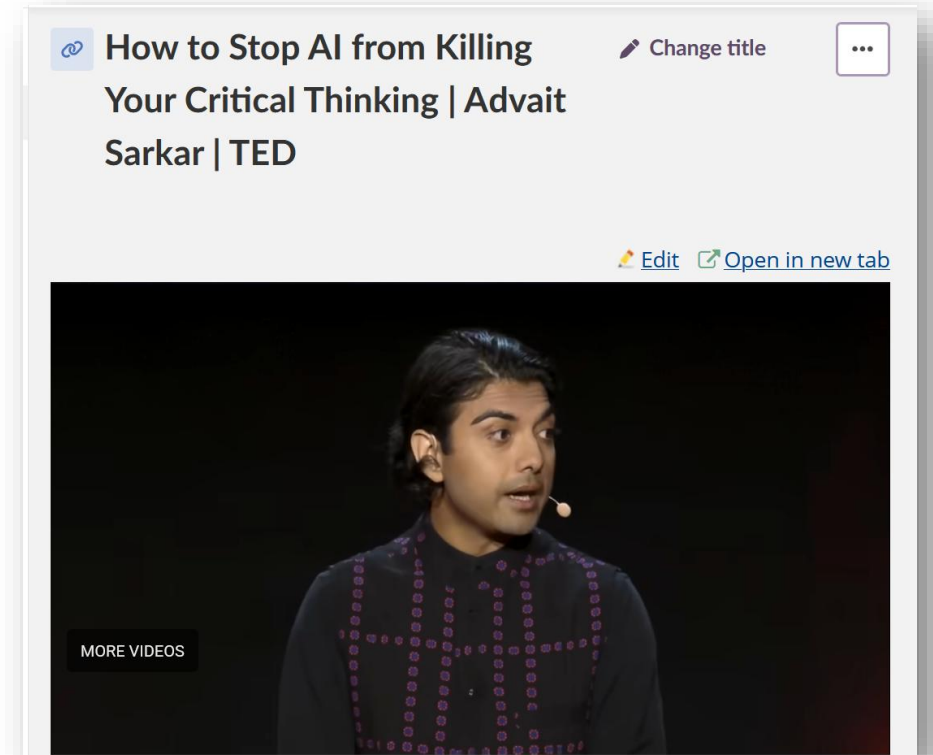
- Series of eight experiments ( $n = 1,917$ ) tested peoples' ability to distinguish between internal knowledge—encoded and retrieved from their own memories—and external knowledge found on the internet
- Shows that looking facts up does allow you to answer questions more correctly – that leads to the erroneous assumption that you also \*know\* it – but short-term memory is not long-term memory (btw- that's why we do unaided exams)
- Critically: People that google information also perceive themselves as being smart and having a better memory than most other people
- Spoiler: that is not the case



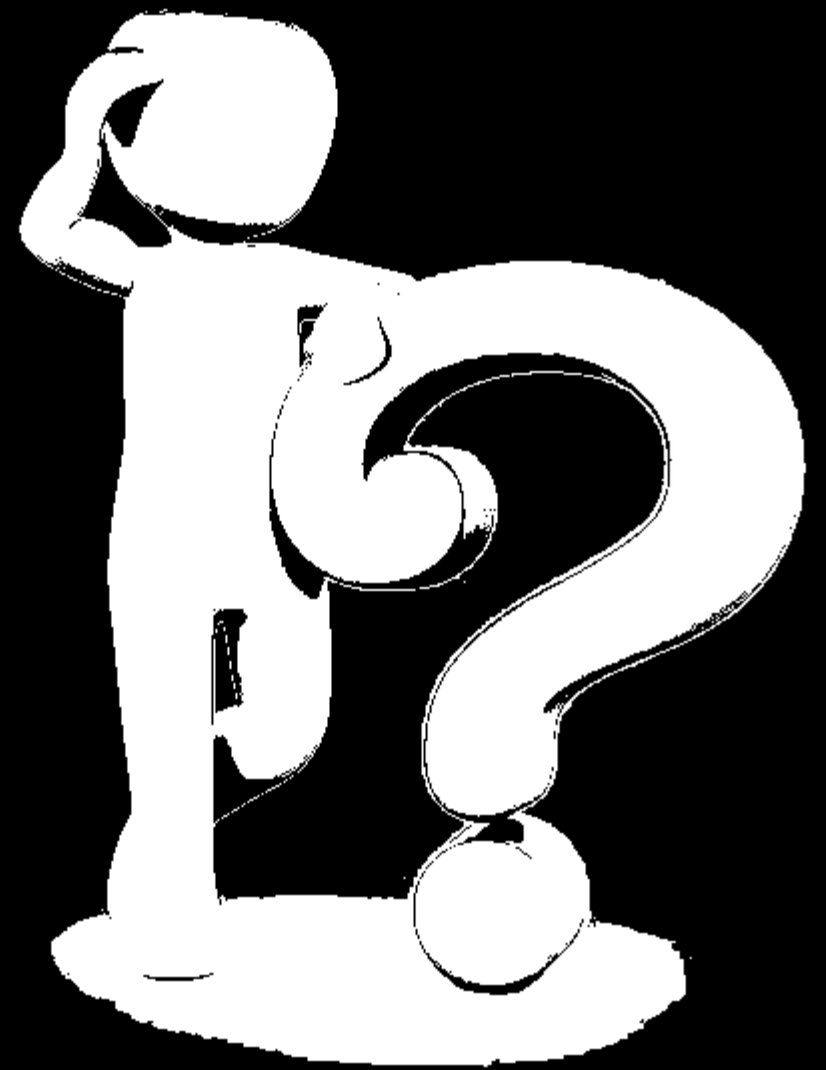


# But: When does it matter? (Mo et al., 2026; Pearson, 2025)

- We all engage in “cognitive offloading” – we share things with others to not have to memorize all of them ourselves (#Christmas presents)
- Plus: Meta analyses indicate that AI-enhanced learning can have a positive effect on learning outcomes (however, several of the included studies are very small - should be interpreted with care)
- So the question is maybe: What kind of smart do we need – and when can we “offload” tasks to AI?
- **What could be criteria for “brain-optimized” AI use?**



**What are your questions  
so far?**



# Then I hope, you know...

- ...have an initial insight into human's memory works
- ...have a broad understanding of how humans learn
- ...have discussed how using LLMs can support but also impair your learning
- ...have discussed how we perceived the world (and how that relates to memory and learning)



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## #2 Learning

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