Cognitive Models

CS 347
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Last time

When users cannot predict how input controls affect outputs the interface is terrible

- True of black box AI
- True of humans
- Will **always** be true until we can develop ways to explain the mapping from inputs to outputs

Approaches to improving AI interfaces

- Allow **conversational turn taking**, Establish **common ground/shared semantics**, Provide **repair mechanisms**
- Deal with *ambiguity of natural language* by **developing other input modalities**
- Enable *iterative refinement*, by **maintaining shared structures**
- Use code as an intermediate language to enable *iterative refinement* via **incremental actions**

Human-Centered AI

Unit 4

Human-Centered AI
Working with Unpredictable Black Boxes

Cognition

Unit 5

cognitive models
visualization
(and don't forget the design cognition that we already covered)

Announcements

Quiz 3 on Wed

- Collaboration
- Human-Centered AI
- Working with Unpredictable Black Boxes
- Cognitive Models

Today

Low-level cognitive models

- The model human processor, GOMS, KLM
- Where are they now?

Cognition in the world: embodied and distributed cognition

Cognitive limitations

Building a better mouse(trap)

[Card and Moran 1988]

Doug Engelbart and Bill English felt that their **mouse was an interim device**, and wanted to make something better

But none of their inventions were actually improving target acquisition speeds

So, Stu Card and Tom Moran tested the mouse in the lab on a variety of pointing tasks

Building a better mouse(trap)

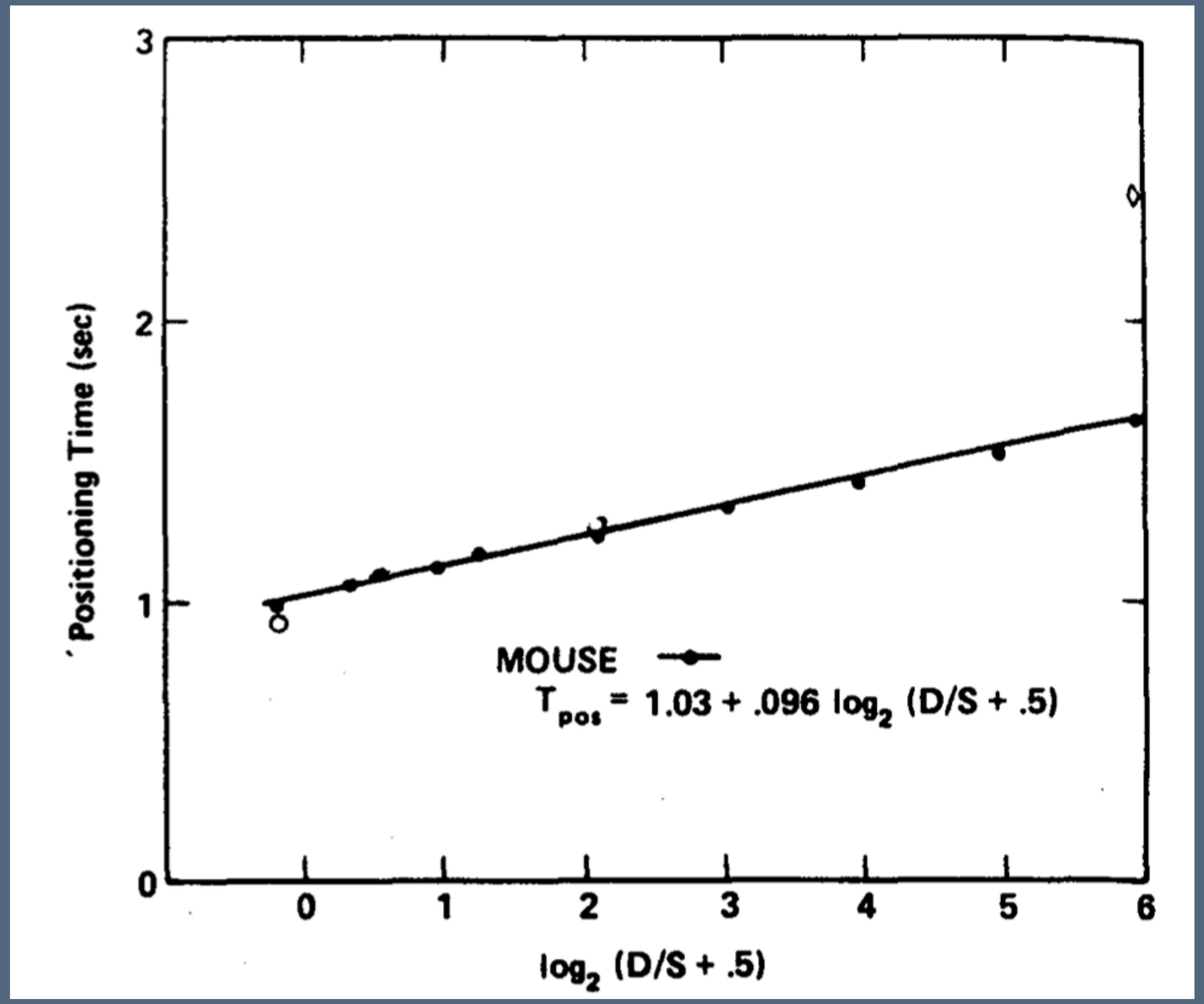
[Card and Moran 1988]

Performance was very well modeled by **Fitts's Law**.
(Fitts's Law is about human pointing, not mouses.)

T = a + b log(D/S +0.5), D = distance, S = tgt. size

Moreover, the mouse's constant of proportionality (**b** = 0.96 sec/bit = 10.4 bits/sec) is approximately the same with the mouse as with the hand alone — **so the mouse is near optimal, you actually can't do better!**

Here, modeling solved a problem that engineering couldn't



Line = Fitts's Law prediction
Dots = measured mouse time

“User technology includes hardware and software techniques […] but it must include a **technical understanding of the user** and of the nature of human-computer interaction. This latter part, **the scientific base of user technology**, is necessary in order to understand **why** interaction techniques are (or are not) successful, to help us **invent** new techniques, and to pave the way for machines that aid humans in performing significant intellectual tasks.”

Model Human Processor

Let's be ambitious!

The Model Human Processor

[Card, Moran and Newell 1983]

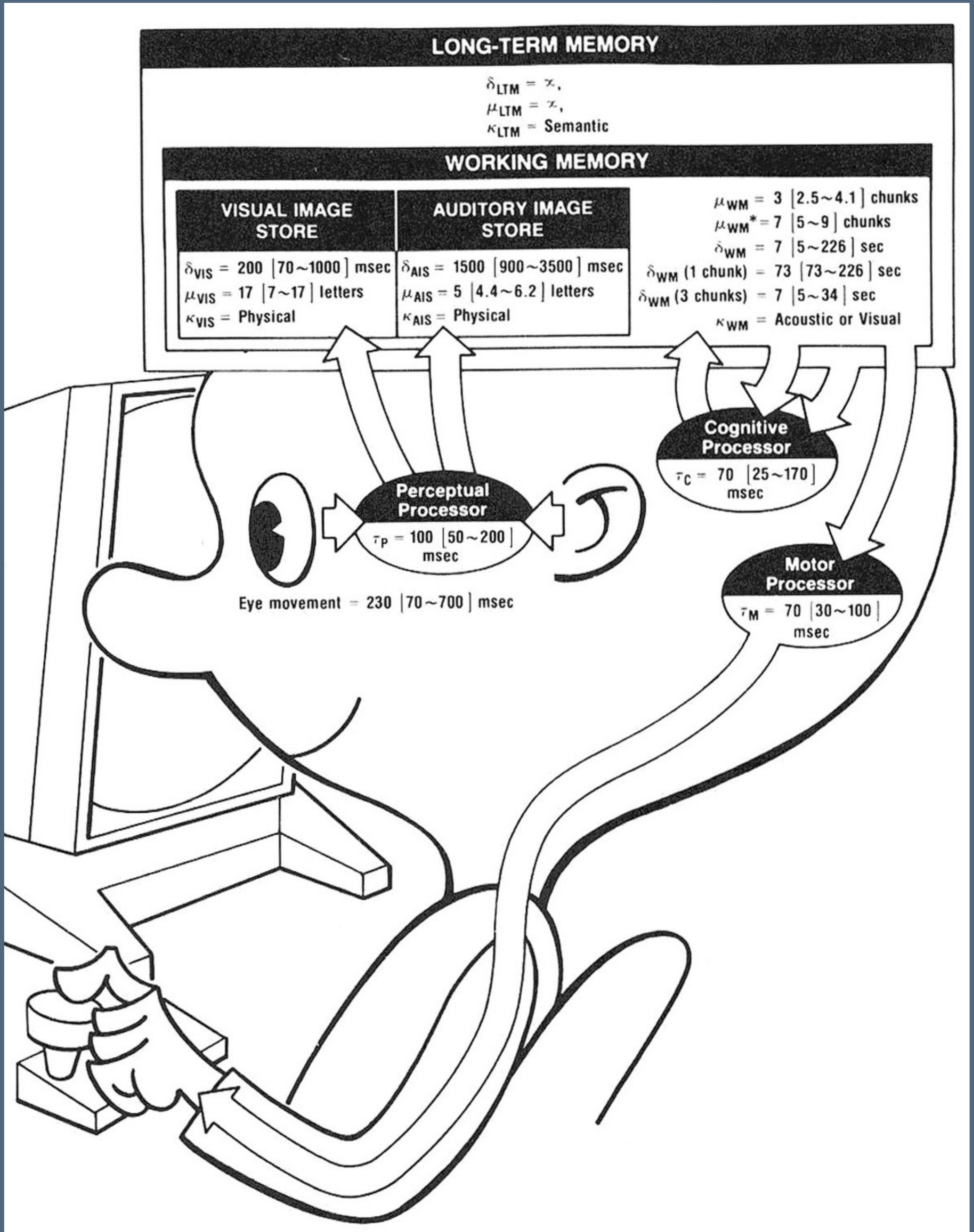
A unified, low-level engineering model of user task completion

Processors

Perception
Cognition
Motor

Memory

Working, Long-term

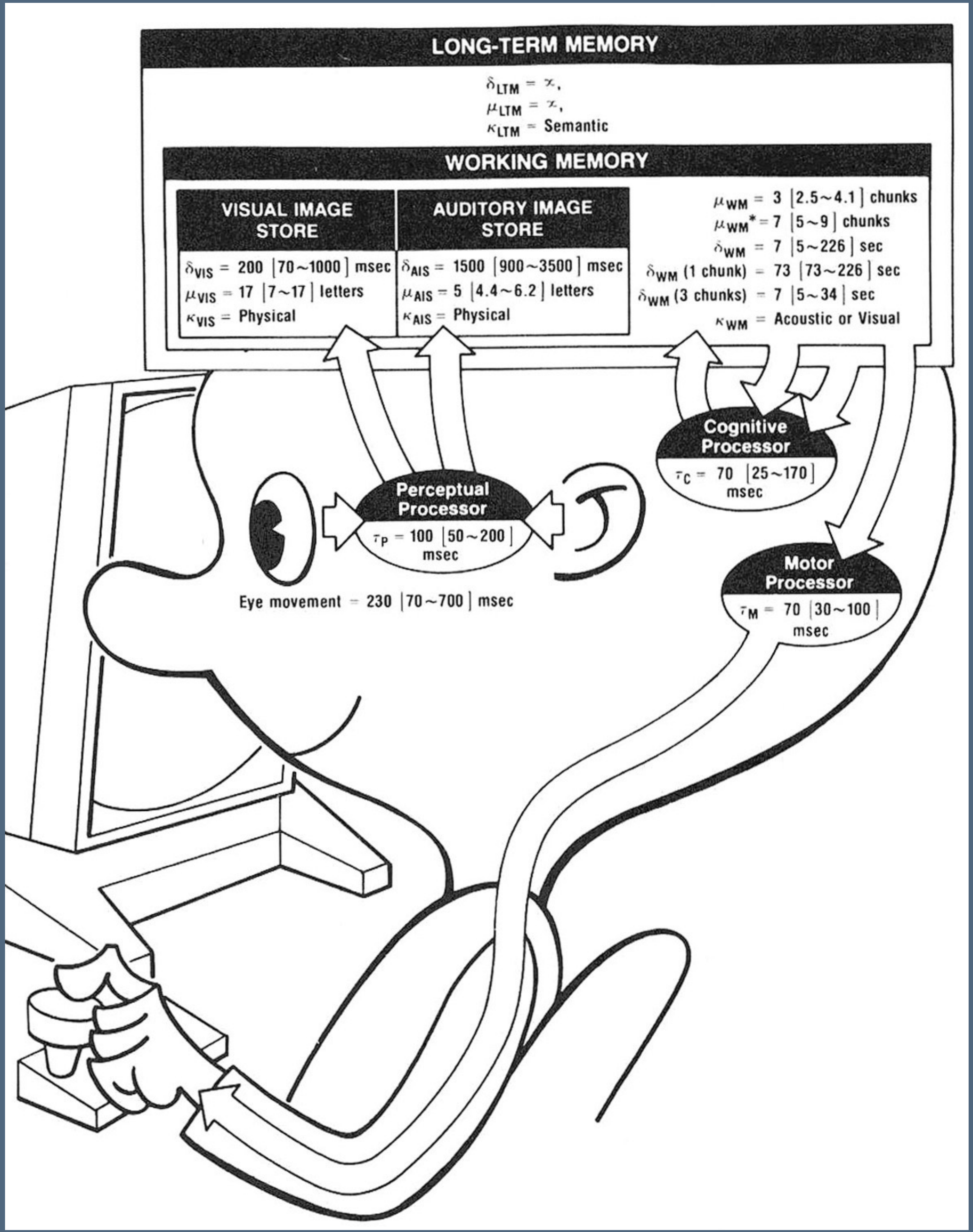


Why Model Humans?

So we can **better understand why** what works works, and **why** what doesn't work is broken

Apply MHP to **predict time and accuracy** of using interface

Apply MHP as a **simulation of human user** (with constraints) **to evaluate** interface designs

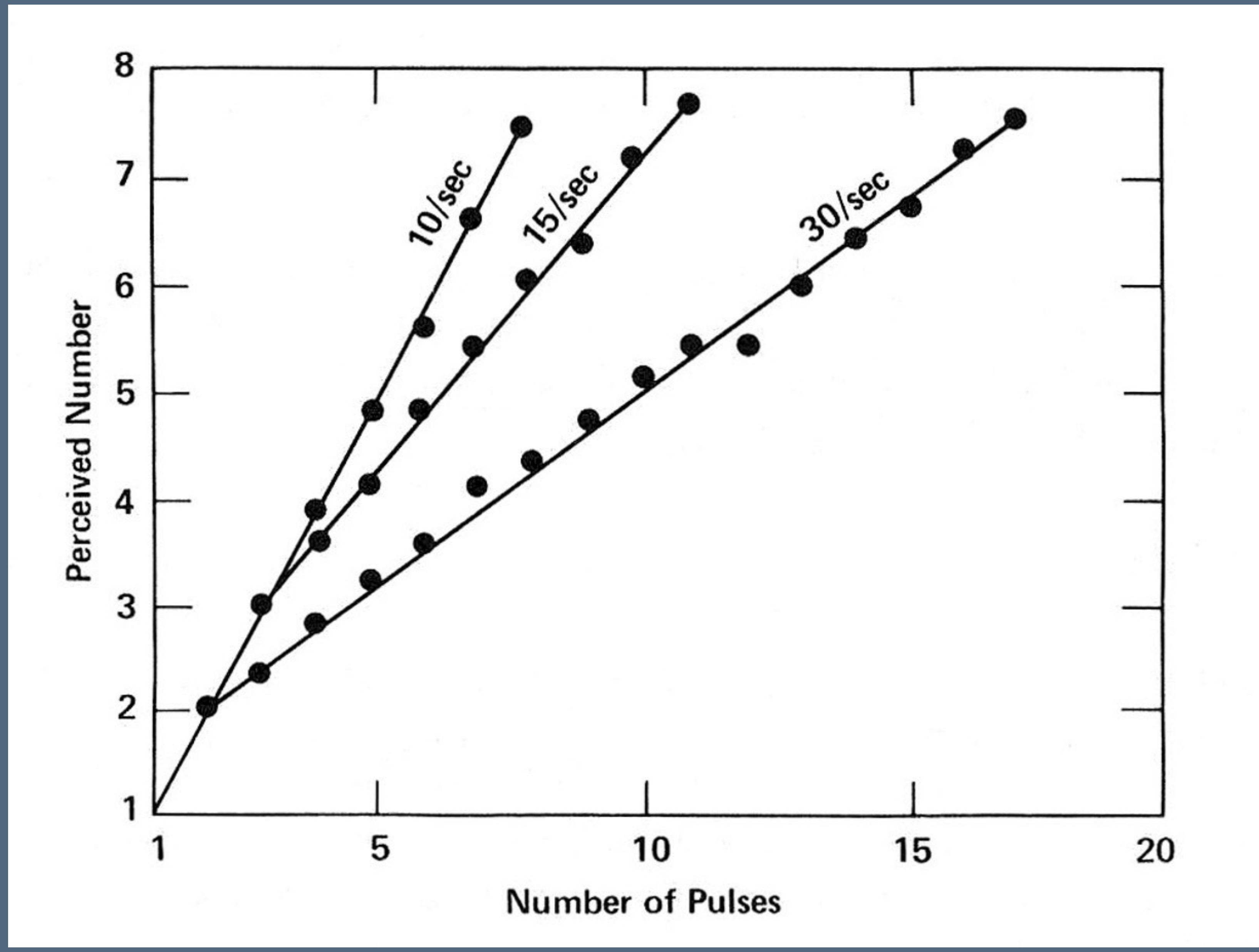


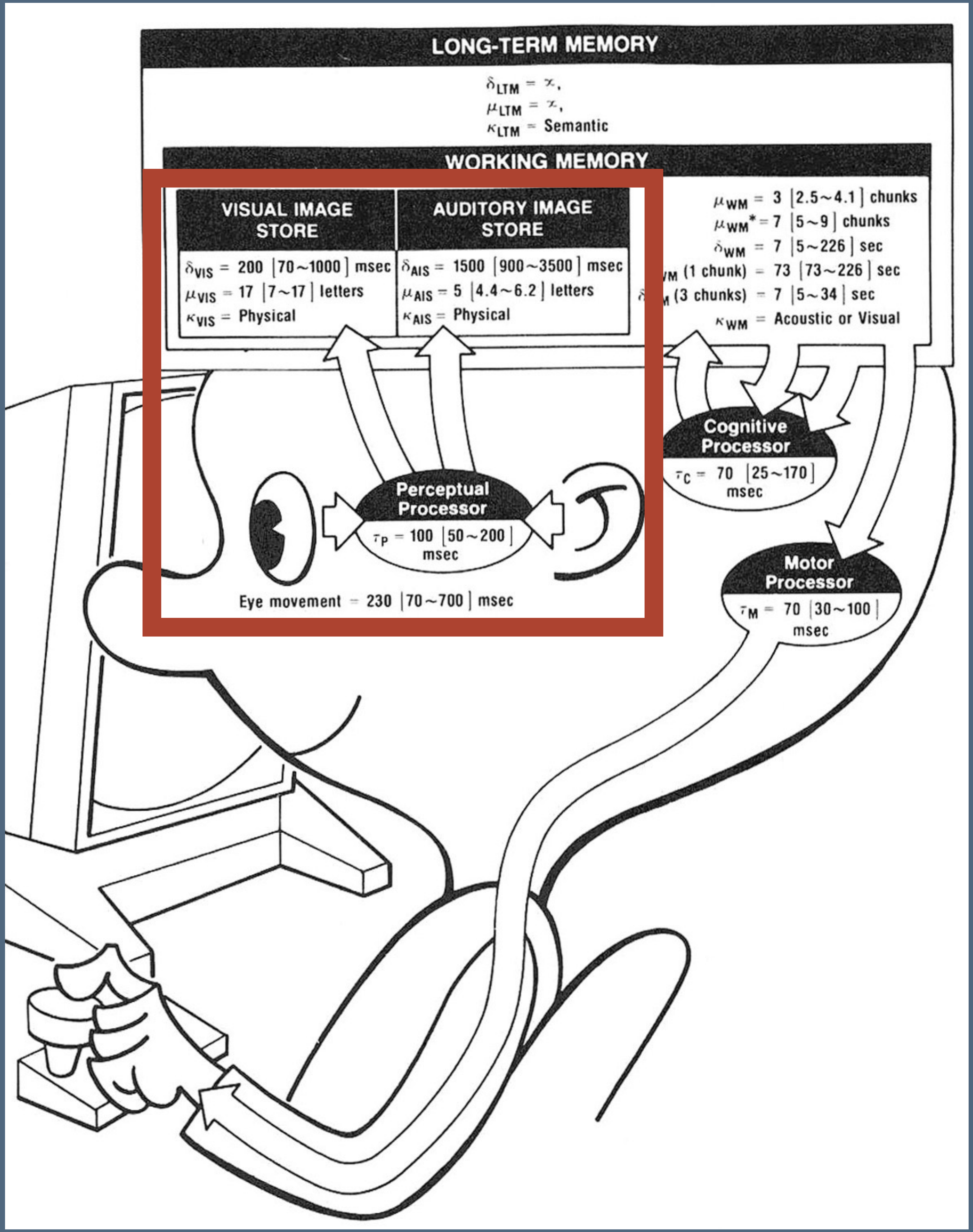
Perceptual Proc.

Time needed to integrate/fuse perceptual experience of the world

T_P = 100 msec (Quantum of experience)

= 10 fps: Rate needed for film to look cts.





Perception of Causality

[Michotte 1946]

What do you see?

Perception of Causality

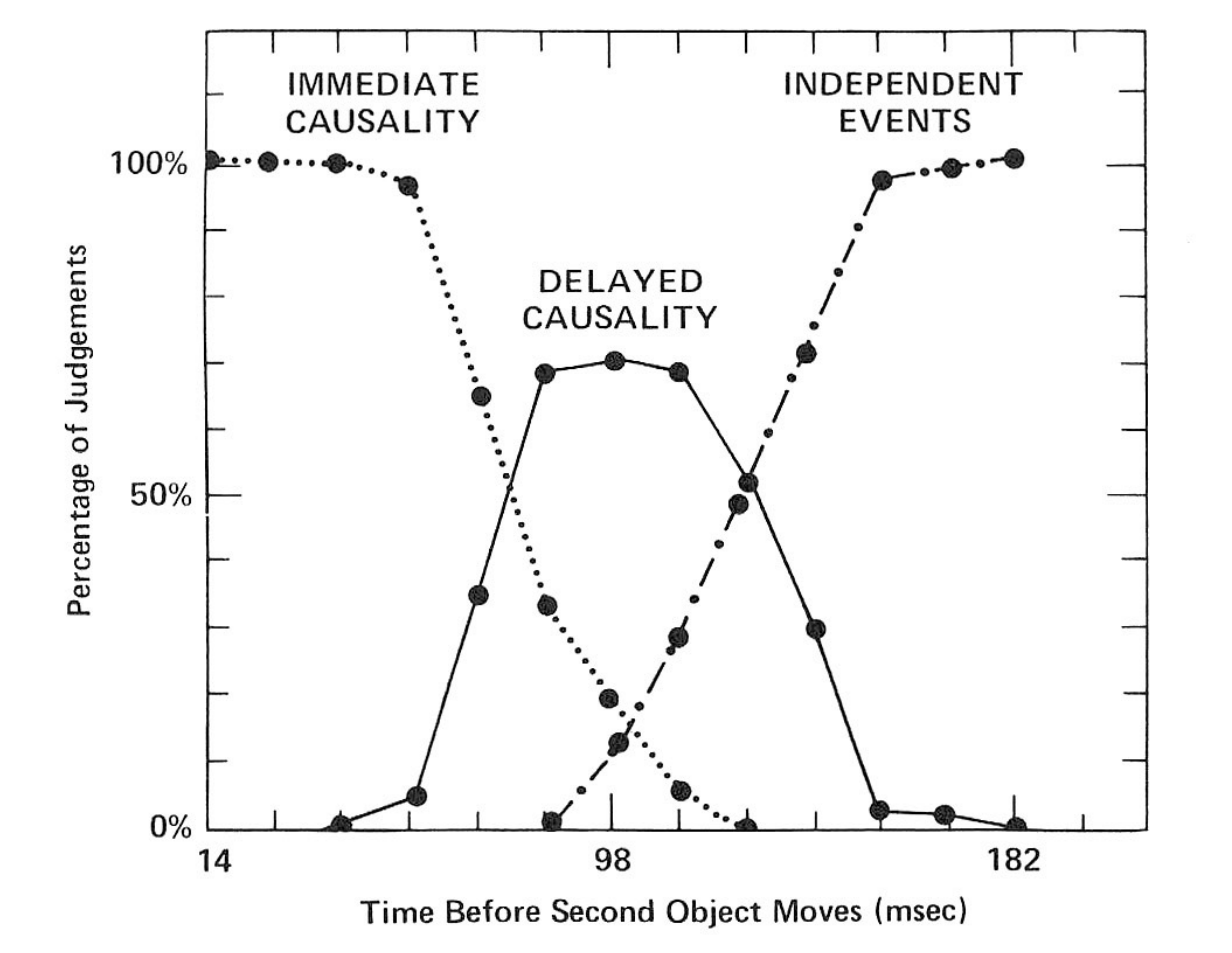
[Michotte 1946]

What do you see?

Perceptual Processor

Time needed to integrate/fuse perceptual experience of the world

- **T_P** = 100 msec (Quantum of experience)
  - = 10 fps: Rate needed for film to look cts.
  - = **Rate needed to imply causality**



Memory

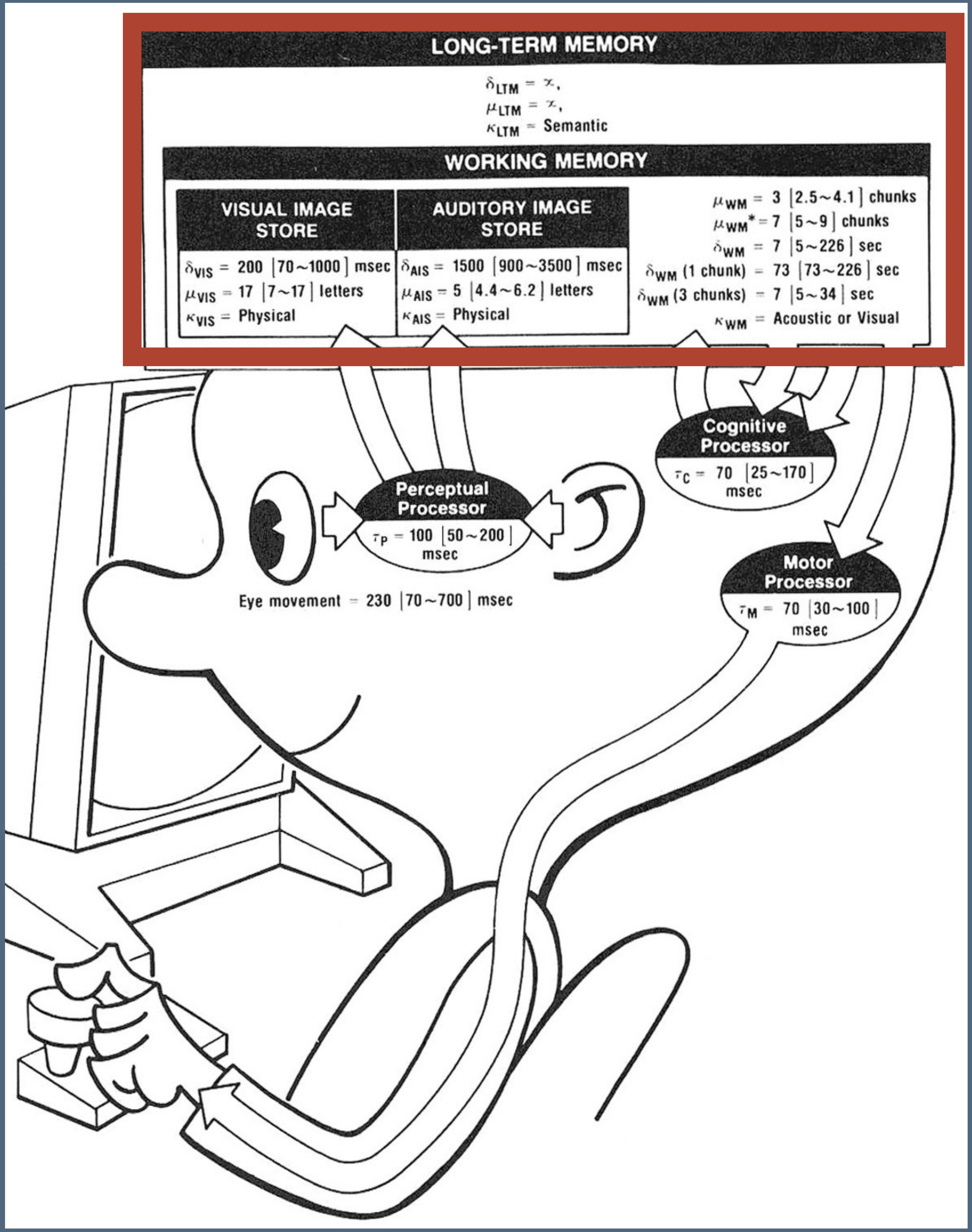
Perceptual processor puts information into (vis/aud/…) **sensory store**

very fast decay 200-1500 msec
small units of information (e.g. letters)

Some info then **chunked** and put into longer decay **working memory**

decay 5-225 sec (content dependent)
7 +/- 2 chunks (e.g. words)

Some info then recoded (semantically) and put into **non-decaying long-term memory**



Working Memory

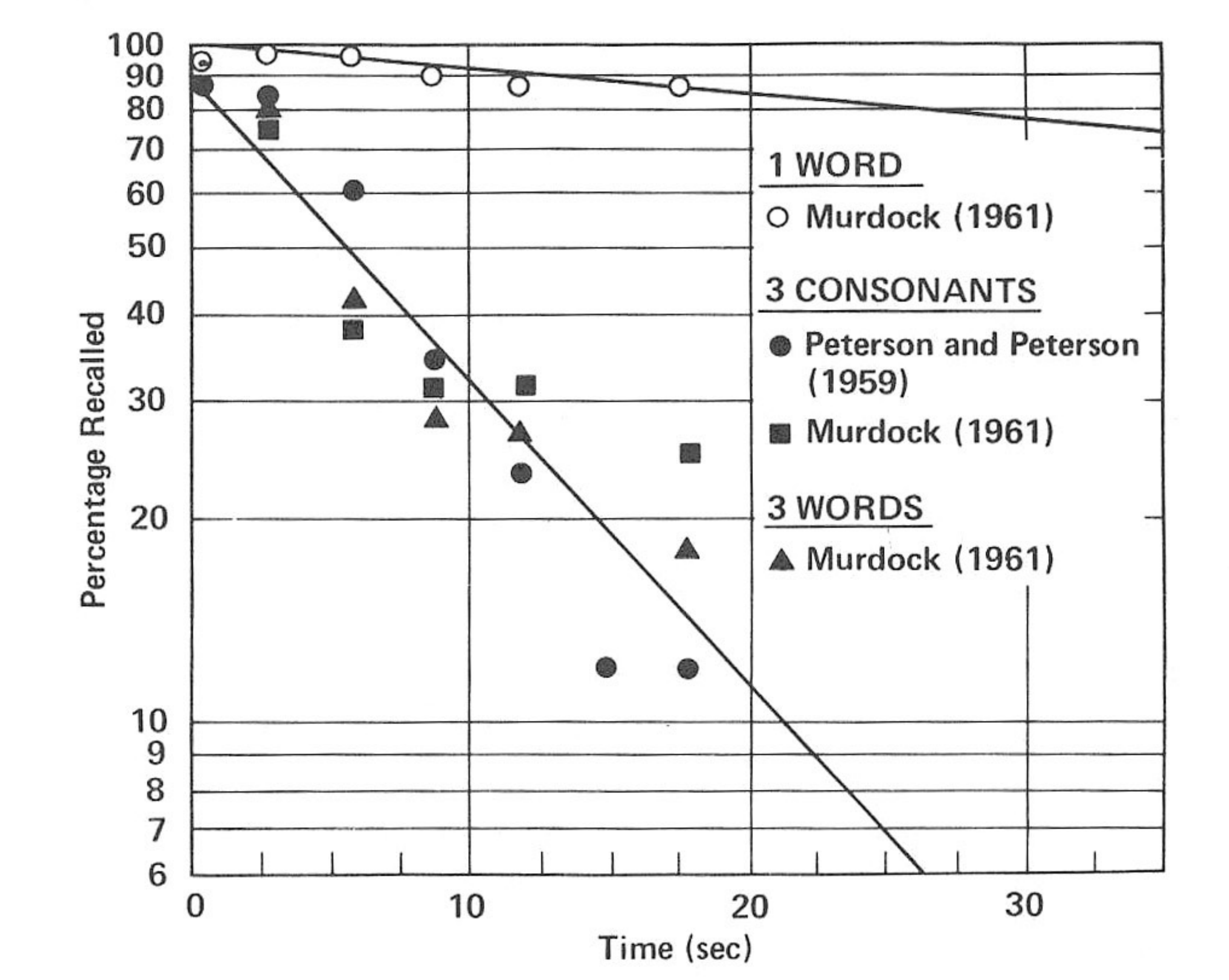
Decay 5-225 sec is content dependent

- 1 chunk (73 sec)
- 3 chunks (7 sec)

Can use **maintenance rehearsal** (e.g. rote repetition) to retain in WM

Attention span

- Interruption time > decay time



Long Term Memory

Very large capacity (semantic encoding)

Associative access (context at insertion is key for retrieval)

- Fast read: 70msec
- Expensive write: 10s

Can move WM to LTM via **rehearsal** and **elaboration**

- Rehearsal (e.g. rote repetition)
- Elaboration to recode information semantically
  - relate new material to material already learned
  - link to existing knowlege or categories
  - attach meaning (e.g. make a story)

LTM & Forgetting

Causes for not remembering an item?

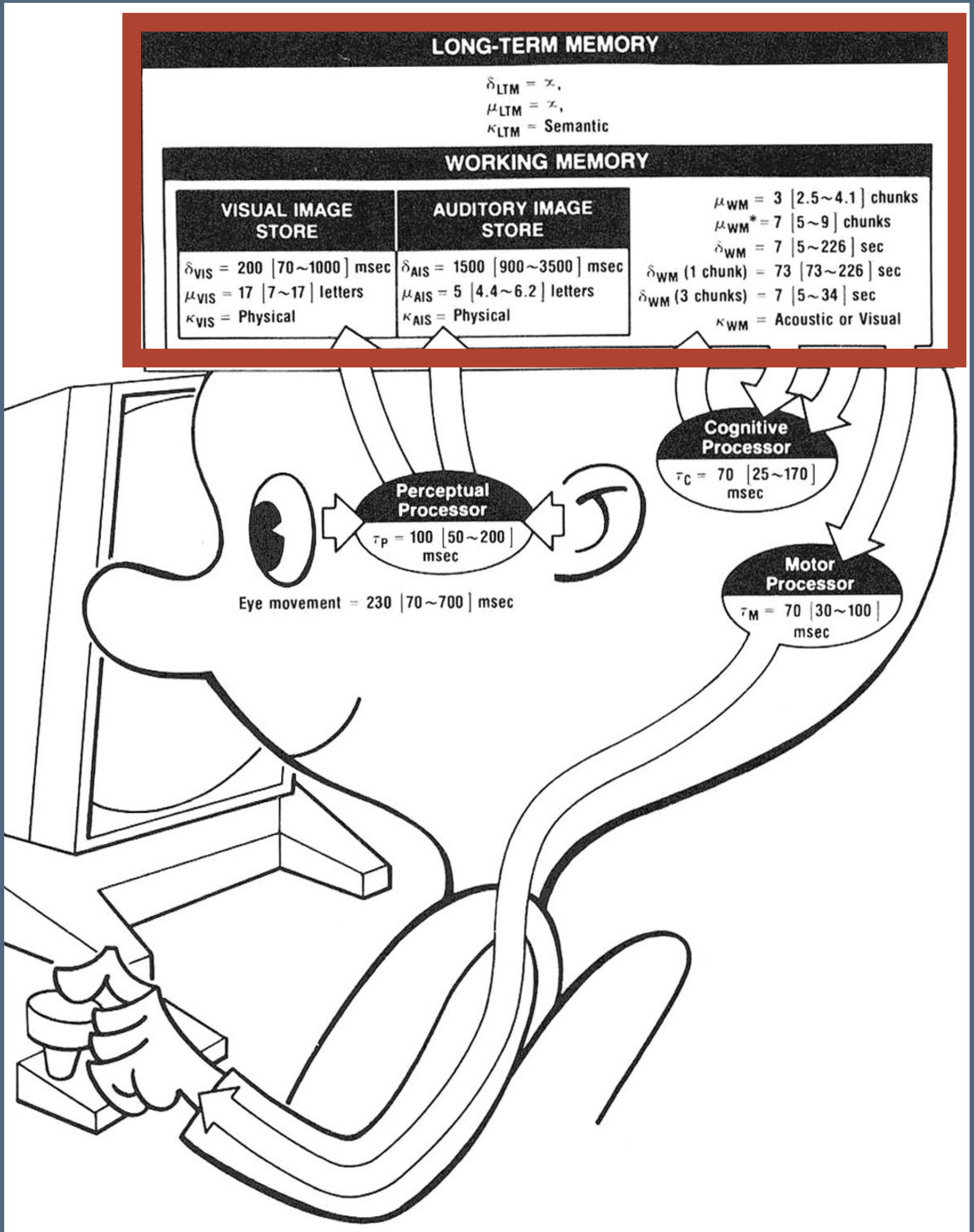
1. **Encoding failure:** never stored
2. **Storage failure:** was stored but now gone
3. **Retrieval failure:** Can't get out of storage

Interference model of forgetting

One item reduces ability to retrieve another

Proactive interference: Earlier learning reduces ability to retrieve later info

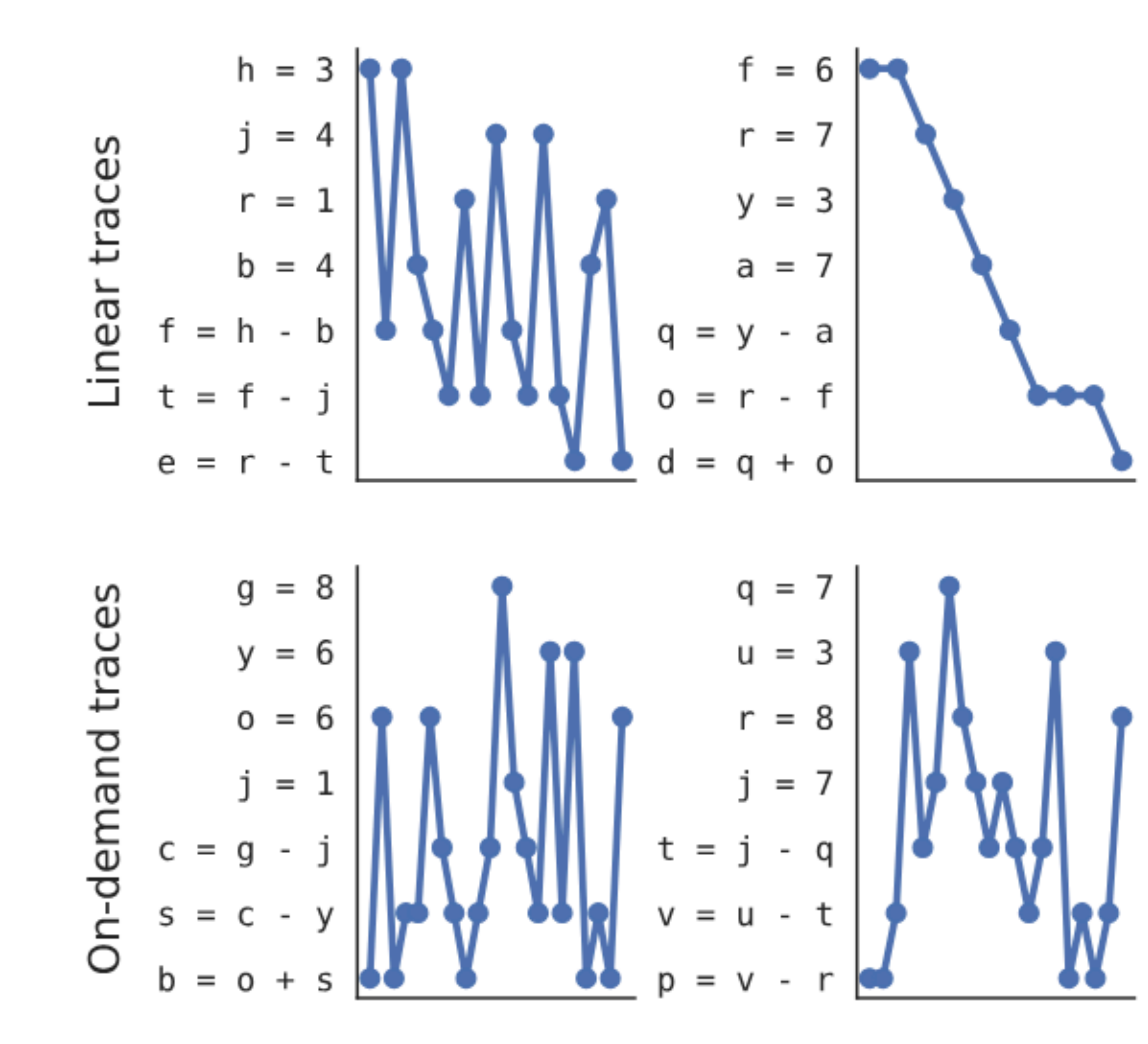
Retroactive interference: Later learning reduces the ability to retrieve earlier info.



WM and Program Tracing

YOU READ THIS

[Crichton, Agrawala, Hanrahan 2021]



Examines how people trace simple programs

- Order in which lines are exposed (linear vs. on-demand)
- How often need to re-visit a line already seen

WM holds ~7 (variable, value) pairs

Both linear and on-demand orderings frequently used

People make different WM errors depending on ordering strategy with more errors using on-demand

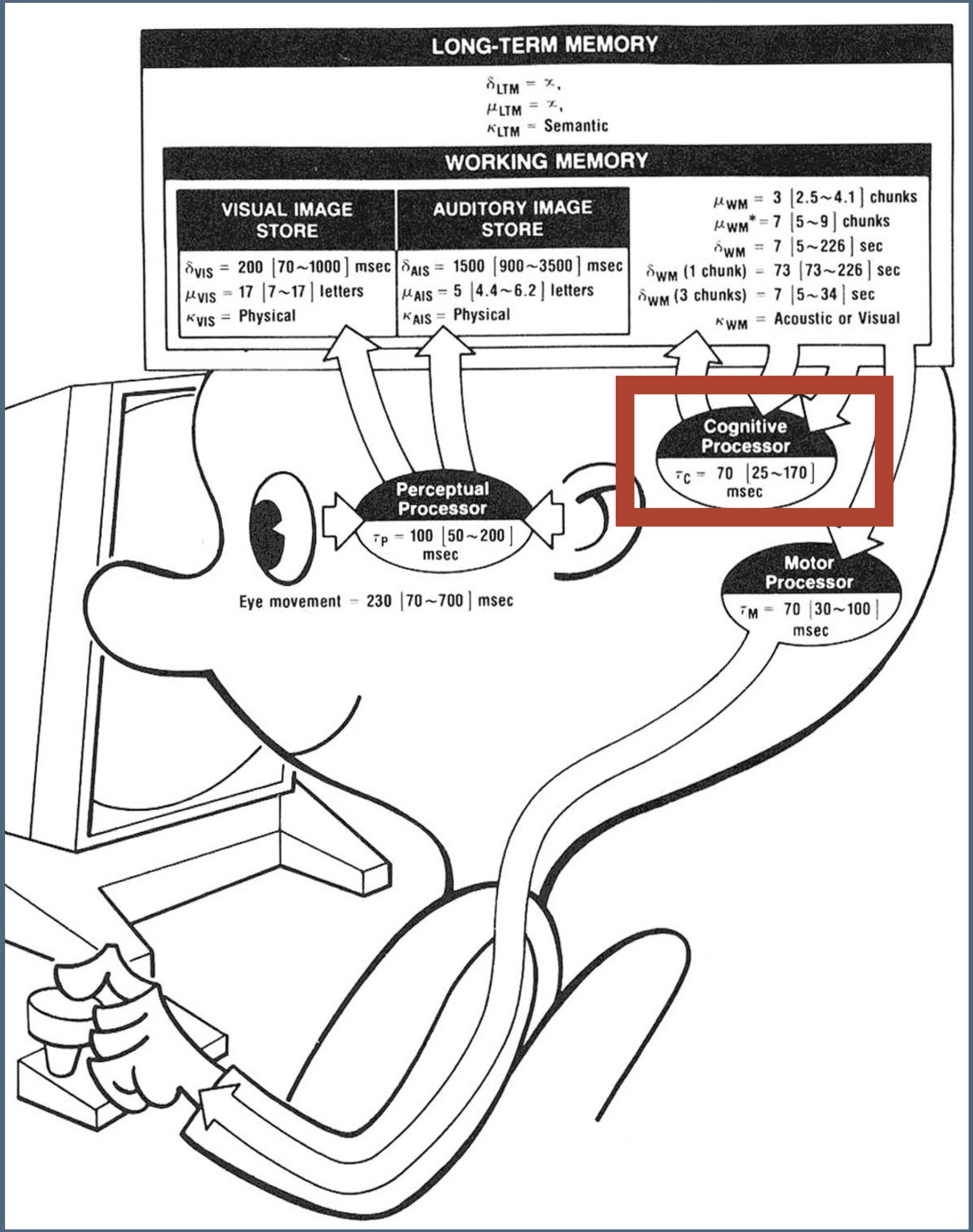
Cognitive Proc.

Time needed to observe WM and operate on it (e.g. check if 2 chunks match)

τ_C = 70 msec

Fundamentally serial

1 locus of attention at a time

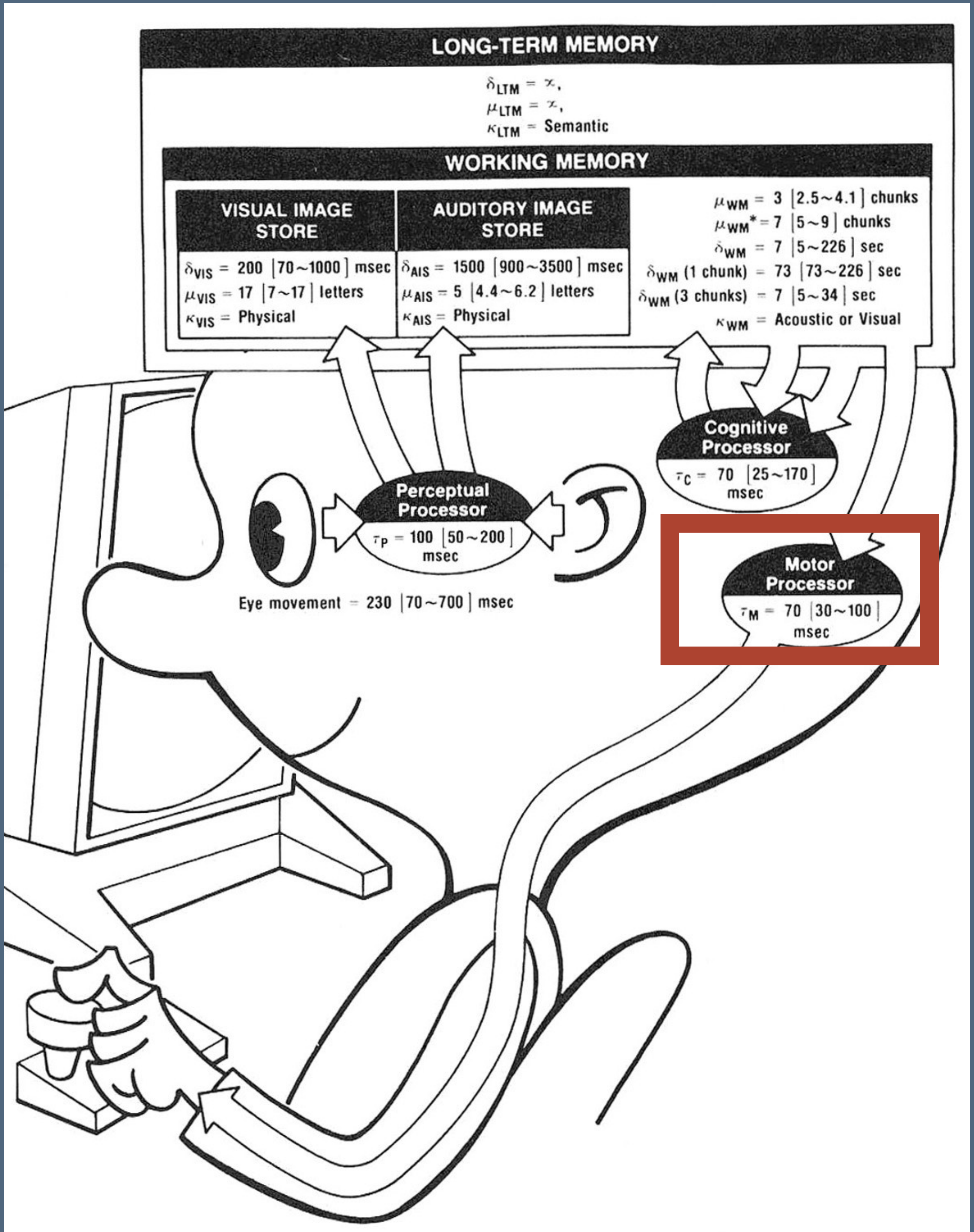


Motor Proc.

Time needed to take input cmd from cognitive proc. & execute it with body

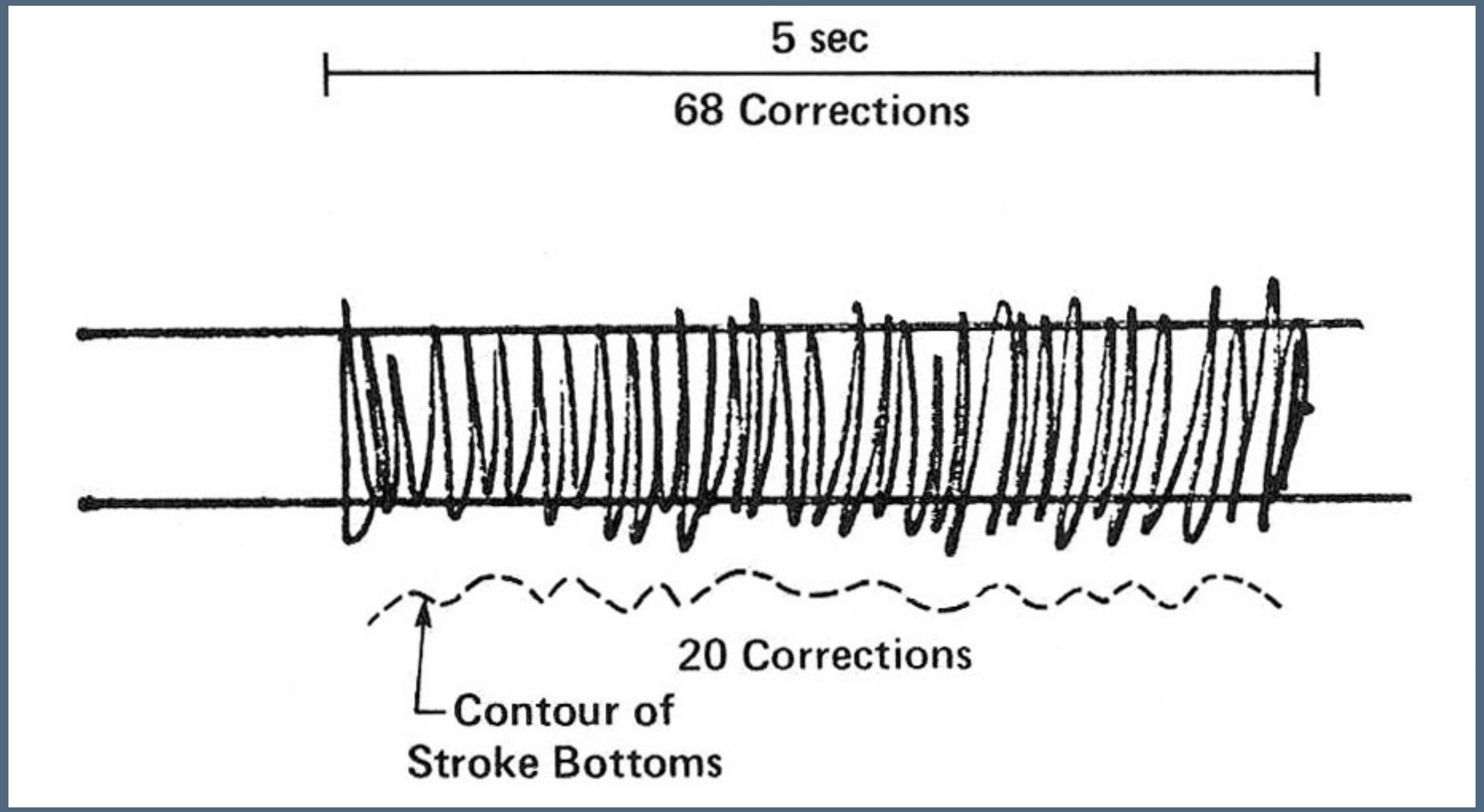
T_M = 70 msec

Pianist (up to 16 finger movements/sec)



Motor Experiment

Ask person move pen back and forth as quickly as possible:



Open loop: 68 reversals/5sec = 74 msec/reversal

Closed loop: Subj. perceives if stroke is staying within lines, sends info to cognitive proc. which can advise the motor processor to adjust.

Total time = $\mathbf{T_P} + \mathbf{T_C} + \mathbf{T_M}$ = ~240msec

20 corrections/5 = 250msec

Using the Model Human Processor

Low level task: I will flash 2 symbols ***x*** and **y** on screen serially, press a key if they are both numbers

Clocks starts when 2nd symbol **y** is flashed
Move symbol **y** into visual store WM — Tp

Recognize both symbols ***x*** and **y** as codes — + Tc

Classify the both codes as numbers — + Tc

Match the fact that they are both numbers — + Tc

Initiate motor response — + Tc

Process motor command — +Tm

Approx 450 (180-980) msec

GOMS

Goals: what the user seeks to achieve

Operators: low-level operations

Methods: compositions of operations together

Selection rules: how to decide between multiple available methods

Given this specification, a system can trace a path that a user would take through a system to achieve their goal and report how long it would take

KLM [Card, Moran and Newell 1980] [Raskin 2000]

YOU READ THIS

Keystroke Level Model: a specific model in the GOMS family. Designed to be quick and easy to use, no need to build a prototype.

Provides a bunch of operators and methods: not GOMS from scratch

Six operators: push a key, point to a target on the display, moving hands between keyboard/mouse/etc., drawing a line (seems extraneous to me), making a decision about the next step, waiting for system response

Operator	Time
Key/Click	0.20
Point	1.1
Homing	0.4
Draw	$.9n_D + .16\, l_D$
Mental	1.35
Sys. **R**esp.	Depends

Raskin's KLM Rules

YOU READ THIS

First break task into H,P, K,D, R (then use rules)

R0: Insert M

In front of all K

In front of all P's selecting a command (not setting args)

R1: Remove M btw fully anticipated operators

PMK to PK

R2,R3: if MKs form cog. unit delete all Ms but first

typing "4564.23": MKMKMKMKMKMKMK to MKKKKKKK

typing "enter" "enter": MKMK to MKK (redundant terminator)

R4: if K terminates freq. used fixed length string (e.g. cmd) delete M in front of it

typing "cd" "enter": MKKMK to MKKK

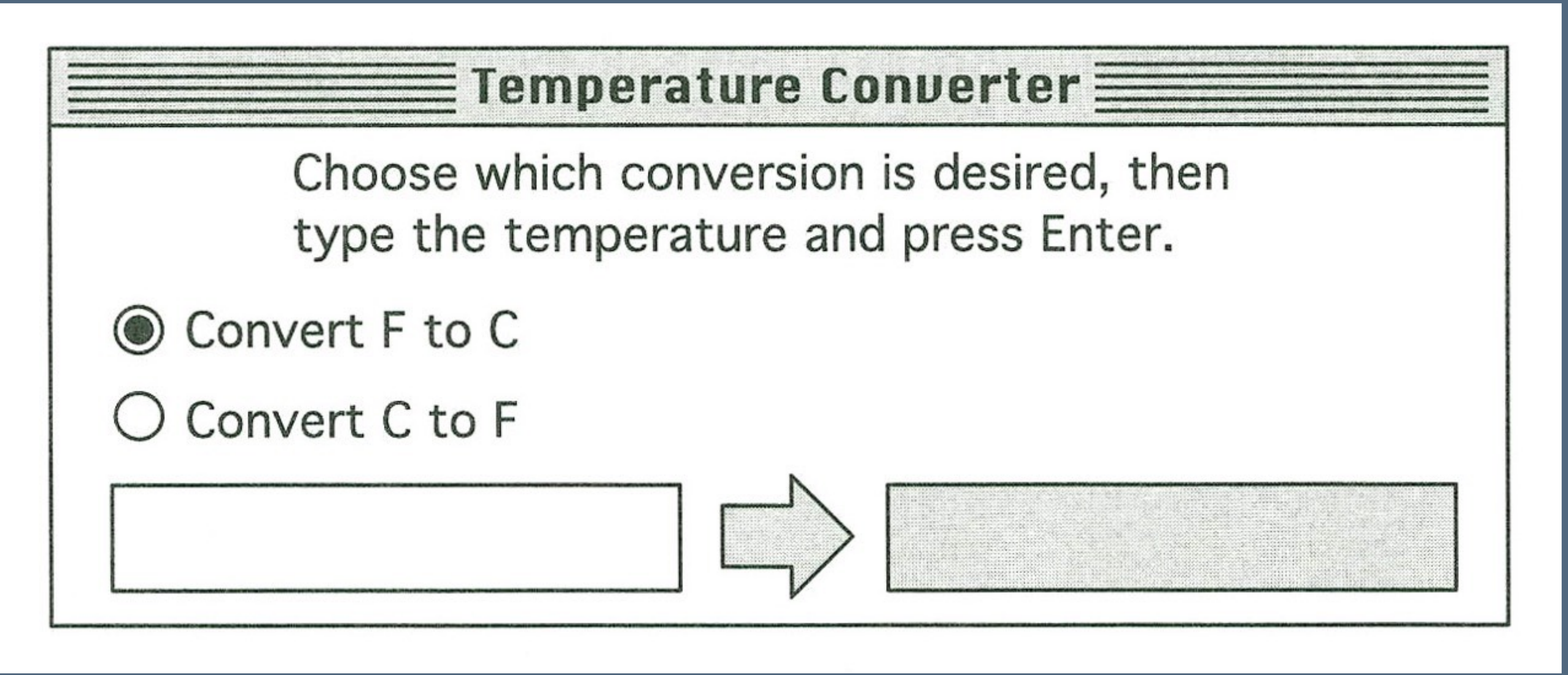
typing "cd" "class" "enter": MKKKMKKKKKMK (do not remove last M)

Operator	Time
Key/Click	0.20
Point	1.1
Homing	0.4
Draw	$.9n_D + .16\, l_D$
Mental	1.35
Sys. **R**esp.	Depends

Converting Temperature

Convert 92.5

Assume focus on dialog, hands at keyboard, typing enters text into text field



Assuming goal C to F

H PK H KKKK K to H MPMK H MKMKMKMK MK to H MPK H MKKKK MK (7.15sec)

Assuming goal F to C

KKKK K to MKMKMKMK MK to MKKKK MK (3.7sec)

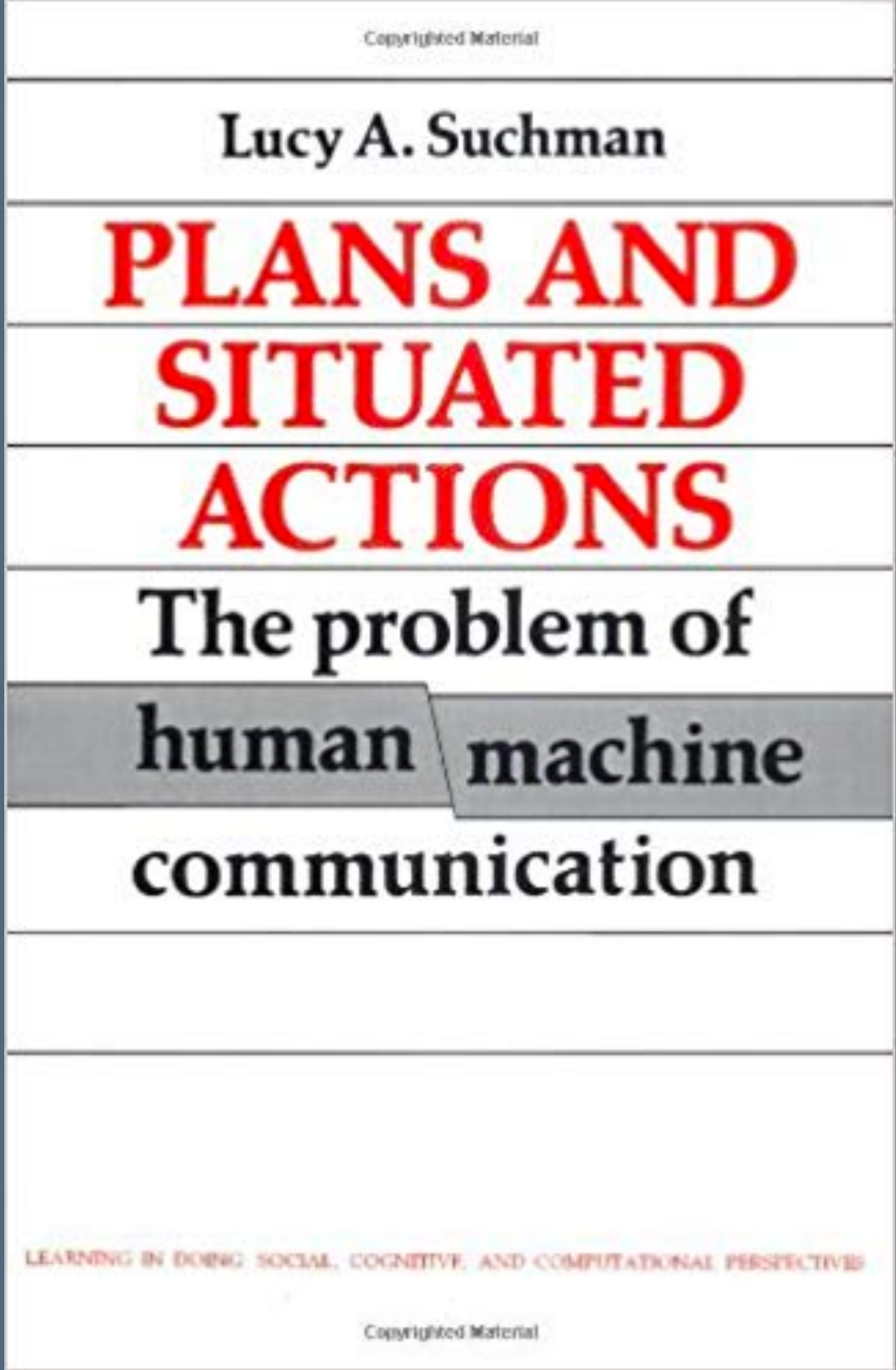
Avg time: 5.4sec

Where are they now?

Models as inhuman models of how we act

Plans cannot succeed in complex environments, which instead require constant reflection and reorientation [Suchman 1988]

Anthropological comparison: how people perform wayfinding



GOMS Sensitive to Methods & Operators

In GOMS **researcher defines operators** and **methods**. Need to be **careful** to make sure they are **appropriate to task** and **context**

- "there's no accounting for taste" — GOMS will not object to a ***baroque*** set of operations that a user might never use in practice
- Outcomes will depend strongly on exactly which operators and methods you define and make available to the model

GOMS Relatively Quantitative

GOMS explicitly **capture low-level cognitive behaviors** of interest **quantitatively**

- The Model Human Processor estimates were based on careful lab studies
- But **absolute numbers less reliable than relative values**

Can be less work than a user study

Today

Low-level cognitive models (e.g. GOMS and KLM) have fallen out of favor, largely because they require **substantial effort** to create, vs. directly prototyping

However, for low-level optimizations and interface decisions, cognitive models can be very useful

And, they remain important to HCI as an example of how **grounding our designs in psychological methods** and results can lead to more effective approaches and insights

Thinking in the world

Cognition for ubiquitous computing environments

Recall: "Pictures Under Glass"

[Victor 2011]

Embodied cognition

[Dourish 2004; Klemmer, Hartmann, Takayama 2006]

Our cognition leverages **embodiment**—our bodies:

- We learn through interaction with the world
- We leverage the environments around us to make us smarter
- We communicate our intent through much broader mechanisms than just our fingertips: consider musicians, dancers, construction workers, professors on stage trying to get your attention

Epistemic action

[Kirsh and Maglio 1994]

Tetris as an example task to study cognition

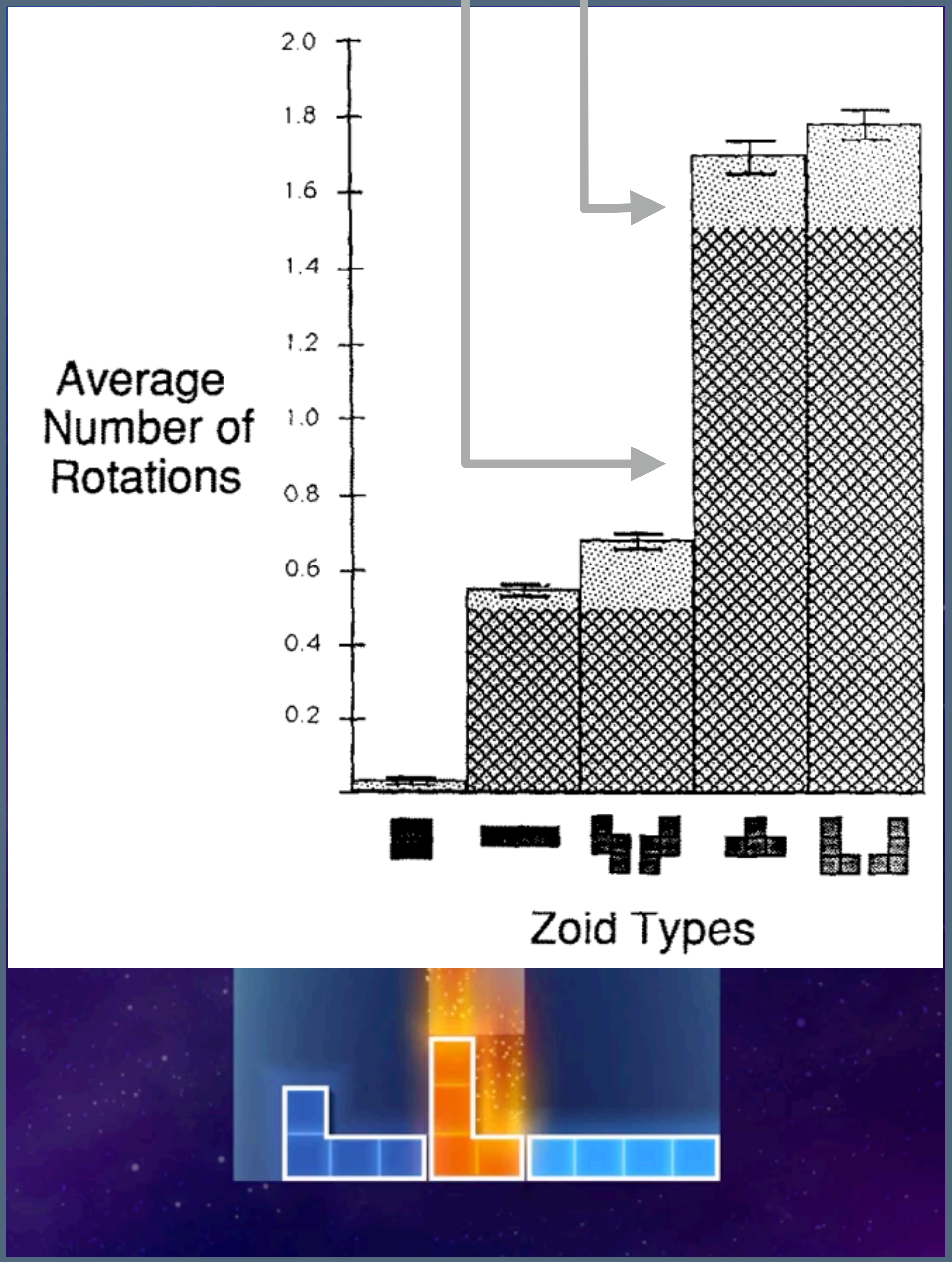
Players see a piece, rotate it, and drop it into position

However, experts perform more rotations than strictly needed to position the piece. Why?

We perform actions in the world to uncover information that is hard for us to compute mentally

Hatched area: required to position the piece

Gray area: extraneous rotations



Distributed cognition

[Hutchins 1995]

Theory: social and physical environments, not just people, can exhibit intelligence

Source: ethnography on the navigation bridge of Navy ships

> Intelligent navigation is **emergent** — from people who coordinate via structured codes, and from their tools
>
> **Intelligent navigation does not reside within any single individual**

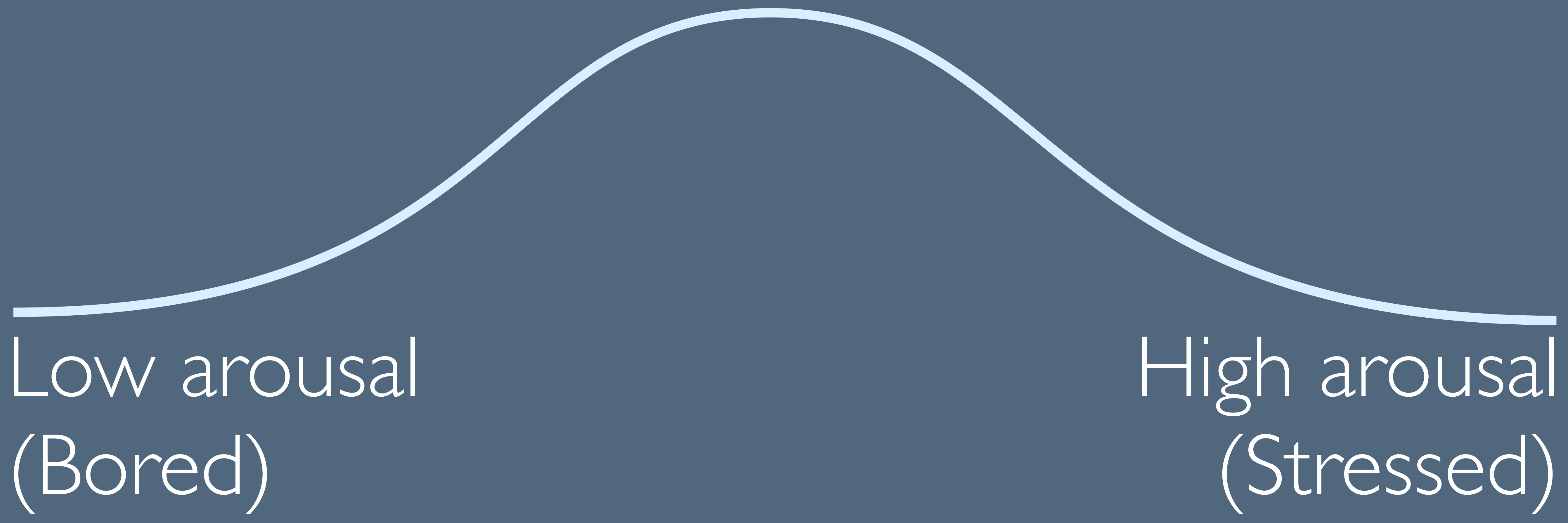
Implication: when analyzing a system, **look for cognition that arises between people or between people and artifacts**

Cognitive limitations

Information overload

As we get more and more information in our environments, we cease being able to make effective use of it — our decision making stops improving or even gets worse

Yerkes-Dodson Law: as arousal (not volume of information) increases, performance increases, but only to a point [Yerkes and Dodson 1908]



Multitasking has costs

People have ~10 different working spheres per day, and spend 11.5 min per working sphere before switching [González and Mark 2004]

- When someone gets interrupted, they take 25 minutes on average before resuming [Mark, González, and Harris 2005]

People who self-report as high multitaskers are actually worse at multitasking [Ophir et al. 2009]

- Proposed mechanism: worse at filtering out irrelevant stimuli

Summary

Cognitive models create **computational proxies of human behavior**, to help us characterize and understand how we will engage with a piece of technology

Model human processor, GOMS, KLM

Thinking in the world requires an understanding of cognition as well: **embodied cognition** emphasizes how we think with our bodies, whereas **distributed cognition** emphasizes how we think with the environment

When our cognition is overloaded, performance decreases

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