How to handle LLMs in your research

Pablo Mosteiro, Ayoub Bagheri

Partly generated with help of Qwen/Qwen2.5-7B-Instruct and moonshotai/Kimi-K2-Instruct-0905 via together and groq, respectively (HuggingChat).

Department of Methodology & Statistics

2026-01-13

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Today's Agenda

- Introduction (5 min)

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- AI, ML, and LLMs (10 min)

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- Conclusion (5 min)

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About us

https://nlp.sites.uu.nl/

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- **Goal**: Assess prior knowledge and create baseline understanding

Artificial Intelligence, ML, and LLMs: Key Definitions

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- Computer systems performing tasks requiring human intelligence

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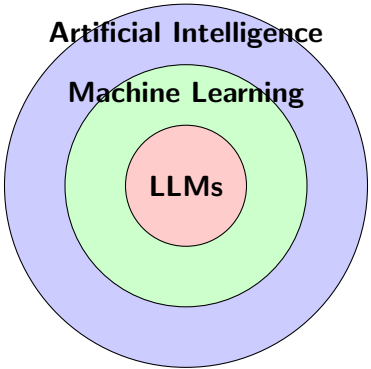
- Examples: GPT, Claude, Qwen, Mistral

AI vs ML vs LLM: The Relationship



LLMs are a specific type of ML,
which is a subset of AI

Model Learning Process: Training Phase

Training Phase

- Model learns patterns from large datasets

Example: LLM learns that "cat" often appears with "dog" in pet-related contexts

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- Adjusts internal parameters to minimize prediction errors
- Requires massive computational resources
- Can take weeks or months for large models

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Key insight: Good models generalize to new data, not just memorize training examples

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- Prevent overfitting (memorizing training data)
- Tune hyperparameters for optimal performance

Key insight: Good models generalize to new data, not just memorize training examples

Model Learning Process: Biases

Common Biases in LLMs

- **Training data bias:** Reflects biases in source material

Real-world impact: Biased models can perpetuate harmful stereotypes

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Common Biases in LLMs

- **Training data bias:** Reflects biases in source material
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- **Confirmation bias:** Reinforces existing beliefs
- **Temporal bias:** Becomes outdated as language/society changes

Real-world impact: Biased models can perpetuate harmful stereotypes

What is Generative AI?

Definition: AI that creates new content (text, images, code, audio)
Key Features:

- Creates novel outputs, not just classifies

Examples: ChatGPT (text), DALL-E (images), CodeT5 (code)

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- Generates human-like content

Examples: ChatGPT (text), DALL-E (images), CodeT5 (code)

Generative AI vs. Other Models

Feature	Generative	Discriminative
Primary Task	Create new content	Classify existing data
Output Type	Novel text/images	Labels/categories
Learning Focus	Data distribution	Decision boundaries
Example	GPT, DALL-E	Spam filters, medical diagnosis

Activity: True or False?

Instructions: Raise your hand if you think the statement is TRUE

Statement 1: Generative AI can only work with text

Statement 2: All generative models are also discriminative

Statement 3: Generative AI creates completely original content never seen in training

Statement 4: LLMs are a type of generative AI

Limitations and Risks: Hallucinations

What are hallucinations?

- LLMs generate false or nonsensical information

Example: Asking for "recent studies on X" might return made-up citations
Risk: Researchers might unknowingly use false information

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Limitations and Risks: Hallucinations

What are hallucinations?

- LLMs generate false or nonsensical information
- Appears confident and plausible
- Can include fake citations, non-existent facts

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Limitations and Risks: Bias

Types of Bias

- **Gender bias:** Assumes doctors are male, nurses are female

Activity: Can you identify bias in this LLM output?

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Limitations and Risks: Output Reliability

Reliability Issues

- **Inconsistency:** Same prompt can yield different answers

Best practice: Always verify critical information from multiple sources

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- **Prompt sensitivity:** Small changes affect outputs significantly

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Limitations and Risks: Ethics

Ethical Concerns

- **Data:** Training data may include personal or copyrighted material

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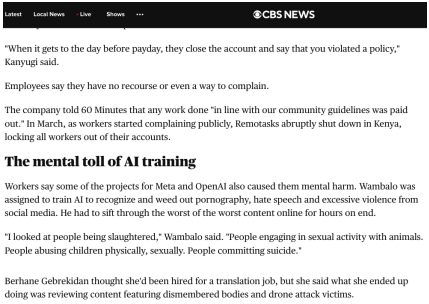

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"When it gets to the day before payday, they close the account and say that you violated a policy," Kanyugi said.

Employees say they have no recourse or even a way to complain.

The company told 60 Minutes that any work done "in line with our community guidelines was paid out." In March, as workers started complaining publicly, Remotasks abruptly shut down in Kenya, locking all workers out of their accounts.

The mental toll of AI training

Workers say some of the projects for Meta and OpenAI also caused them mental harm. Wambalo was assigned to train AI to recognize and weed out pornography, hate speech and excessive violence from social media. He had to sift through the worst of the worst content online for hours on end.

"I looked at people being slaughtered," Wambalo said. "People engaging in sexual activity with animals. People abusing children physically, sexually. People committing suicide."

Berhane Gebrekidan thought she'd been hired for a translation job, but she said what she ended up doing was reviewing content featuring dismembered bodies and drone attack victims.

`https://www.cbsnews.com/news/ai-work-kenya-exploitation-60-minutes` (Nov 2024)

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  "Given both the competitive landscape and the safety implications of large-scale models like GPT-4, this report contains no further details about the architecture (including model size), hardware, training compute, dataset construction, training method, or similar"
  OpenAI: Achiam, J. et al (2024). *GPT-4 Technical Report*.
  `https://arxiv.org/abs/2303.08774`

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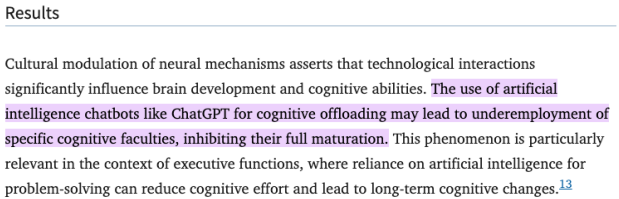
- **Effect on cognition:**



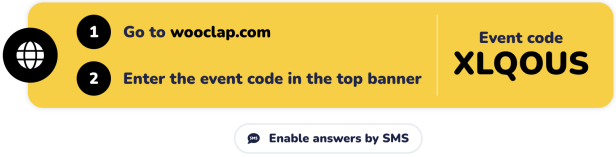
Results

Cultural modulation of neural mechanisms asserts that technological interactions significantly influence brain development and cognitive abilities. The use of artificial intelligence chatbots like ChatGPT for cognitive offloading may lead to underemployment of specific cognitive faculties, inhibiting their full maturation. This phenomenon is particularly relevant in the context of executive functions, where reliance on artificial intelligence for problem-solving can reduce cognitive effort and lead to long-term cognitive changes.[13]

Dubey et al. Redefining Cognitive Domains in the Era of ChatGPT: A Comprehensive Analysis of Artificial Intelligence's Influence and Future Implications. Med Res Arch. 2024 Jun;12(6):5383

Free vs. Paid Systems

Join this Wooclap event



Free vs. Paid Systems

Feature	Free	Paid
Cost	€0	€10-€100+ monthly
Usage Limits	Yes	Higher/none
Model Quality	Basic	Advanced
Response Speed	Slower	Faster
Support	Community	Professional

Free vs. Paid: When to Choose What?

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- Learning or experimenting

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- Advanced features required

LLM Use in Clinical Psychology Research

Appropriate & Inappropriate Uses

- Think-Pair-Share

LLM Use in Clinical Psychology Research: Appropriate Applications

Appropriate Uses

- **Literature review:** Summarizing papers (with verification)

Key: Always maintain human oversight and verification

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- **Writing assistance:** Drafting, editing, proofreading
- **Code generation:** Writing analysis scripts
- **Brainstorming:** Generating research ideas
- **Translation:** Working with multilingual sources

Key: Always maintain human oversight and verification

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- **Original thinking:** Generating truly novel theories
- **Replacing expertise:** They supplement but don't replace researcher knowledge

Effective Prompting: BRAVE(R) Framework

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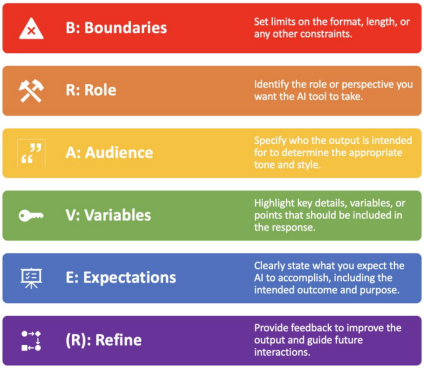
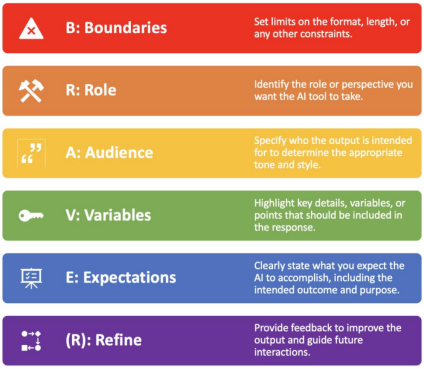


Prompt formulation by Christine Fox, in collaboration with ChatGPT (May 2024).

Effective Prompting: BRAVE(R) Framework



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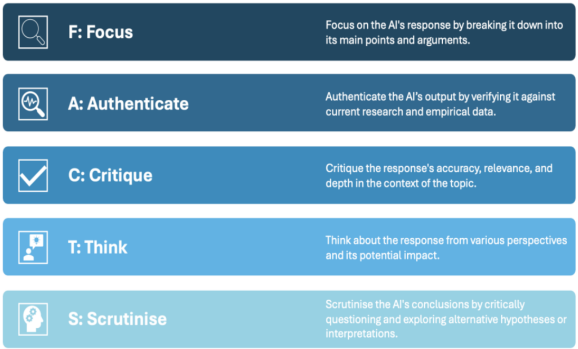
Poor prompt: "Summarize this paper"

Better prompt: "Act as a psychology research assistant [R]. Summarize this paper in 3 bullet points [B] focusing on methodology and findings relevant to cognitive behavioral therapy [V]. Use academic language [A] and APA style [E]."

Key insight: Specific, contextual prompts yield better results

Evaluating and Critically Assessing GenAI Responses

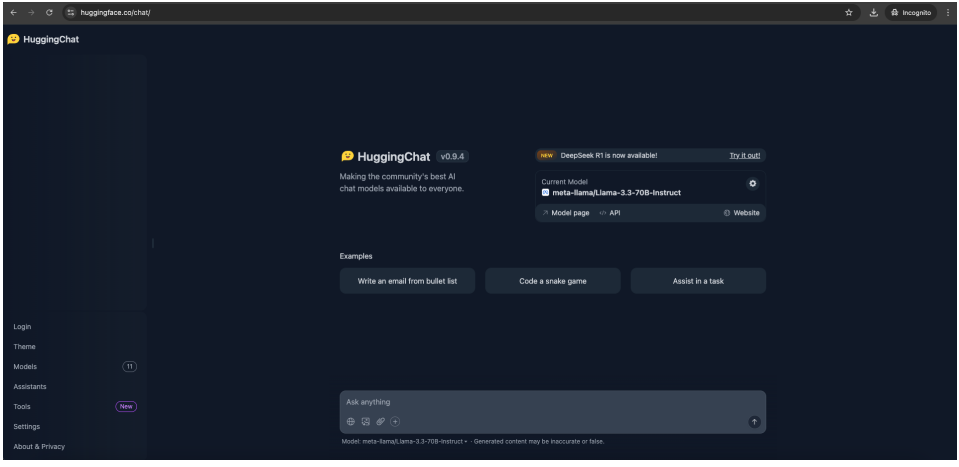
Prompt formulation by Christine Fox, in collaboration with ChatGPT (May 2024).



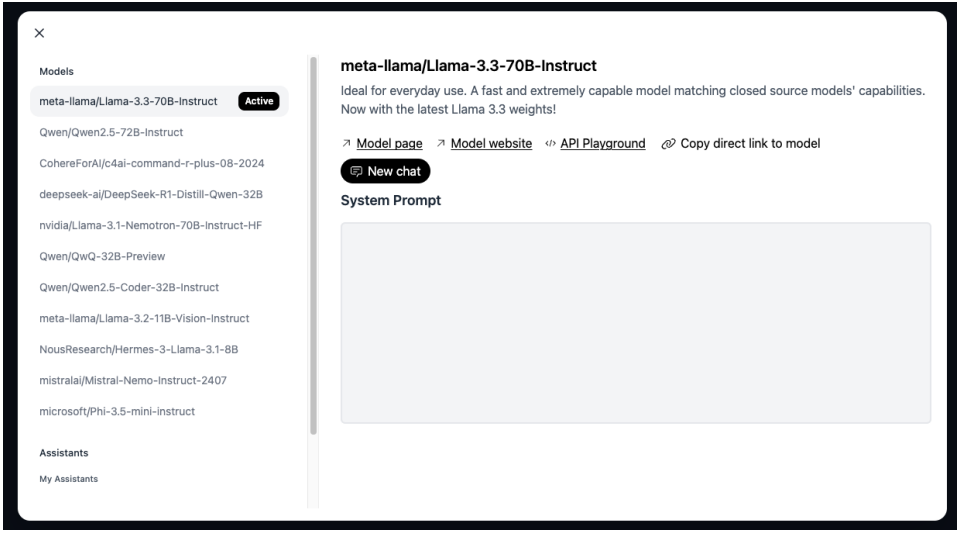
More info:

https://teachersguidegsls.nl/genai/generative-ai-guidelines/

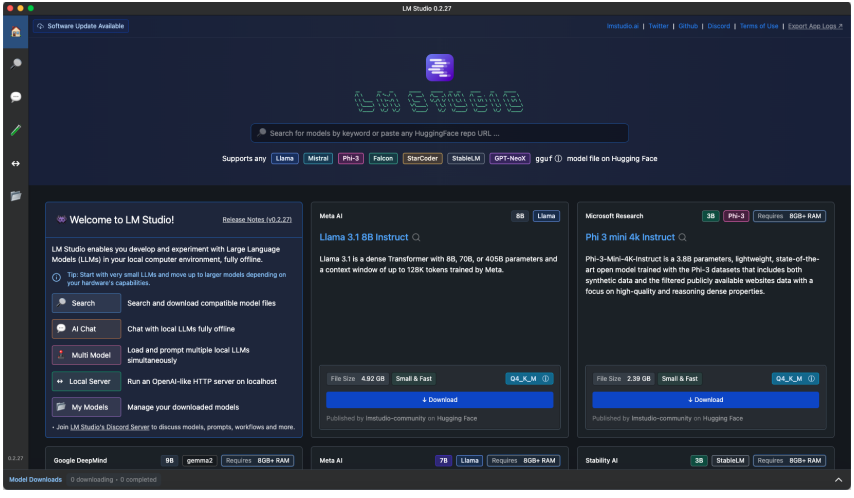
Ways to prompt



Switch models

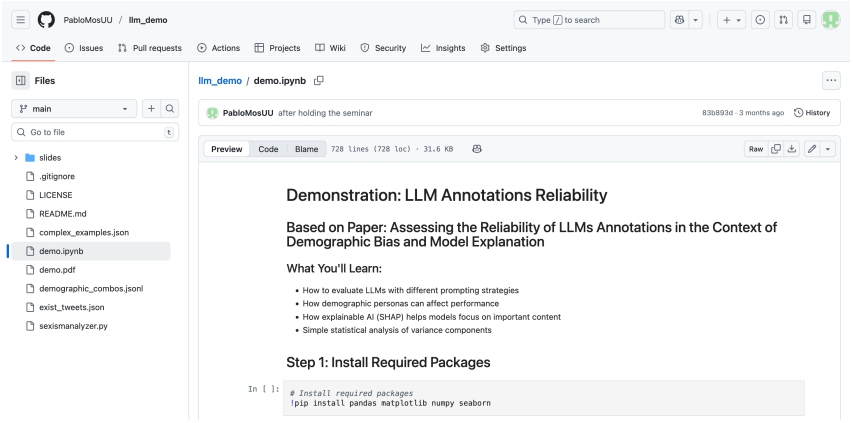


Using an LLM locally (no server)



Versatile platform

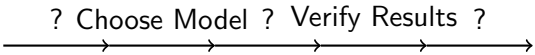
- OpenRouter.ai



https://github.com/PabloMosUU/llm_demo

Activity: Complete the Workflow Diagram

Instructions: Fill in the missing parts of this LLM research workflow



Discussion: What steps are missing? How would you complete this?

Key Takeaways: LLM Workflow

Final Thoughts

Remember:

- LLMs are powerful tools, not replacements for human expertise

Happy researching with AI!

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- Verify outputs and maintain critical thinking

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