

Researching with AI

An introduction

Caleb Lucas

November 21, 2025

Indiana University

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- **Present** *possible* use cases for LLMs in your research pipeline
- **Share** lessons learned from your own experiences with LLMs
- **Begin** a faculty-wide conversation about LLMs ⇒ training

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★ Disclosure: I make no claims about **whether or how or how much** you **should or should not** use AI tools. Caveat emptor.

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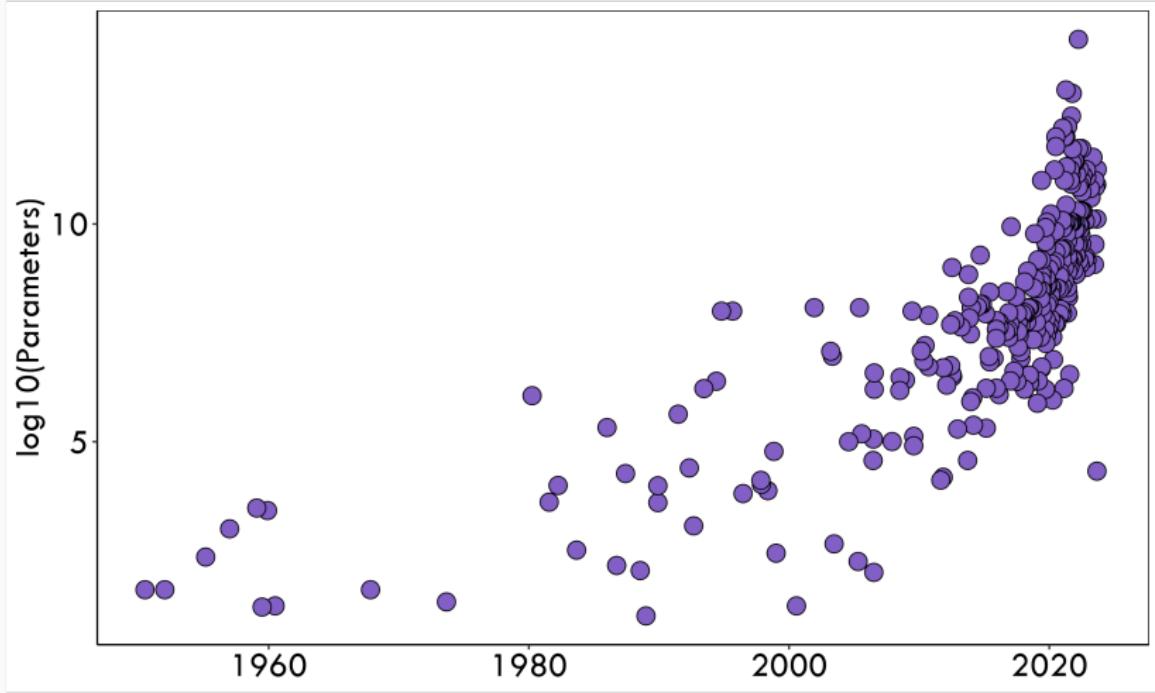
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 - Prepare for a brief, non-technical discussion

But First: Rapid Growth in this Domain



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The quick brown fox jumps over the _____

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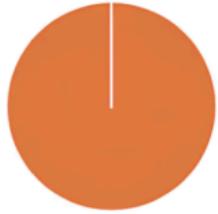
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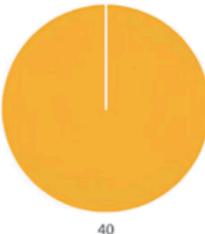
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- How might we learn a model to make this prediction and what data might we give it?

Achieving Conversational AI

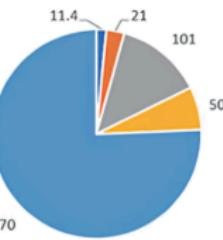
GPT-1



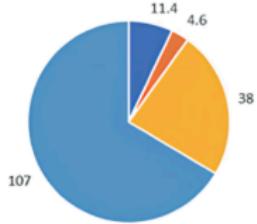
GPT-2



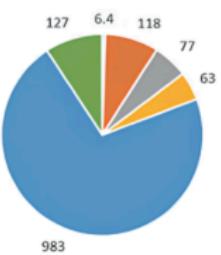
GPT-3



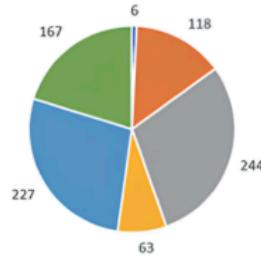
Megatron-11B



MT-NLG



The Pile v1



- Wikipedia
- Books
- Journals
- Reddit links
- CC
- Other

Achieving Conversational AI

Can generate many sequences; squeeze tremendous amounts of information from many disparate sources

- Context
- Next word
- Ignored

The quick brown fox jumps over the

Next-word prediction

Input: The quick brown fox jumps over the



Model: Large Language Model



Word	Probability
power	0.002
big	0.071
lazy	0.085
...	...
hummus	0.001

Next-word prediction

Input: The quick brown fox jumps over the **lazy**



Model: Large Language Model



Word	Probability
apple	0.0002
person	0.001
dog	0.93
...	...
baby	0.001

Next-word prediction

Input: *get_data <-*



Model: Large Language Model



Word	Probability
x	0.1
filter	0.05
function	0.83
...	...
please	0.001

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Do not assume these models are correct or are reasoning effectively.
- **Positive:** The model’s huge number of parameters produce enormous numbers of interactions and embed a great deal of information

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AI Tools for Faculty Tracker

<https://sr.ithaka.org/our-work/generative-ai-product-tracker/>

Generative AI Product Tracker

The Generative AI Product Tracker lists generative AI products that are either marketed specifically towards postsecondary faculty or students or appear to be actively in use by postsecondary faculty or students for teaching, learning, or research activities. The Tracker is a living document, which we update regularly as new products enter the market or new information about existing products becomes available. For more information, see our issue brief, [Generative AI in Higher Ed: The Product Landscape](#). Thanks to Gary Price of Library Journal's infoDOCKET for invaluable help keeping track of new product releases.

You can also access the tracker as a [Google Doc](#).

General Purpose Tools

Name	Purchasing Model	Description	Key Features	Pros	Limitations	Comments	Entry Last Updated
Amazon Bedrock	Users charged for "model inference and customization", see here for details	A service that offers a choice of foundational models through a single API along with capabilities for users to build GenAI applications. "Using Amazon Bedrock, you can easily experiment with and evaluate top FMs for your use case, privately customize them with your data using techniques such as fine-tuning and Retrieval Augmented Generation (RAG), and build agents that execute tasks using your enterprise systems and data sources."	See here for a list of foundational models that Amazon Bedrock supports.				Aug 21 2024
Amazon Titan	See Amazon Bedrock	Family of			Scroll down for		Aug 21

Map a substantive domain: Consensus.app

Can communities successfully manage shared resources themselves?

66 Pro · 2 steps · 20 sources >

Yes, communities can successfully manage shared resources themselves under the right conditions, but success depends on social cohesion, effective governance, and adaptation to local context.

Can communities successfully manage shared resources themselves? N = 7



FIGURE 1 Consensus meter: Most research supports community self-management, with important caveats.

Key Factors for Successful Community Management

- **Design Principles and Social Cohesion:** Empirical research, including Elinor Ostrom's foundational work, shows that communities can avoid the "tragedy of the commons" by developing and enforcing their own rules, especially when they have strong social cohesion and shared identity. Ostrom's eight design principles—such as clear boundaries, participatory rule-making, monitoring, and conflict resolution—are consistently present in successful cases across diverse contexts 8 20 6 2 .
- **Community Monitoring and Participation:** Large-scale experiments and meta-analyses demonstrate that community monitoring reduces overuse and increases satisfaction, even when monitoring is externally initiated. Participation fosters psychological ownership, which supports better management outcomes 4 7 14 .
- **Adaptive Capacity and Governance:** Success is more likely when communities can adapt to changing circum-

Can communities can successfully manage shared resources?

Yes, communities can successfully manage shared resources, often achieving sustainable and equitable outcomes where state or private management might fail. [wikipedia +2](#)

Real-World Examples

- Community forestry in Nepal has empowered local groups to manage forests, improving conservation and livelihoods through clear rules, local engagement, and effective monitoring.

[fastercapital](#)



Successful Models Of Commons Management - FasterCapital

In this page you can find various blogs and articles that are related to this topic:

Successful Models Of Commons Management

Items in Spain have been run by local farmers for centuries, with ensuring sustainable water use and social cohesion. [fastercapital](#)

� in places like Amsterdam and Seoul demonstrate that urban and share resources such as public spaces and tools, benefiting a

[sham.umich](#)

gement

- Clear rules and transparent communication channels are critical, so everyone understands their responsibilities and rights. [consciousbyus +1](#)
- Inclusive decision-making that gives stakeholders a say builds accountability and trust, fostering stewardship and preventing conflicts. [regenerativeeconomics +1](#)

Map a substantive domain: Elicit.com

Can communities successfully manage shared resources without government intervention?

Elicit is building and refining understanding of the research. Your report will become available once all steps are complete. We will email clucas@vaultis.ai when your report is ready (less than 10 minutes).

Show less

View next

Column	Definition	Criteria matches (yes/maybe/no)
Collective Management	Does this study examine community-based collective management rather than individual or private resource management?	● 37 ● 6 ● 7
Community Governance Systems	Does this study focus on formal or informal community institutions, rules, or governance systems for resource management?	● 32 ● 12 ● 6
Community-Based Resource Management	Does this study examine community-based management of common pool resources (natural resources, infrastructure, or other shared assets) with minimal or no direct government control or intervention?	● 27 ● 18 ● 5
Empirical Evidence	Is this an empirical study (including case studies, ethnographic studies, comparative studies, observational studies, systematic reviews, or meta-analyses) rather than a purely theoretical or conceptual paper?	● 20 ● 15 ● 15

Hang tight — you'll be able to chat with this report once it's generated

Status

- Gather sources
50 sources found
- Screen sources
10 sources included
- Extract data
Capturing key metrics and findings from every paper
- Generate report
Summarizing findings

Chat

Map a substantive domain: Elicit.com

NOVEMBER 20, 2025

Can communities successfully manage shared resources without government intervention?

Communities can manage shared resources effectively through self-organized local systems, but require formal government recognition and multi-level governance support to achieve long-term sustainability against external exploitation.

ABSTRACT

Communities can successfully establish and operate resource management systems locally without direct government regulation, achieving positive resource outcomes in diverse contexts including mangrove forests in Thailand *, fisheries in Canada *, and watershed reserves in Honduras *. However, interpreting "without government intervention" as complete independence from higher governance levels proves misleading. Systems operating entirely without government recognition face critical vulnerabilities to external exploitation, as starkly illustrated by the Gulf of California marine reserves where local management increased resource abundance by 40-75% * but attracted regional "roving bandits" who reduced populations by half within one month *. De facto community-developed regimes demonstrate better resource outcomes than imposed systems *, but remain fragile under population pressure, market integration, and difficulty excluding external users *.

The most robust approach combines community autonomy in local decision-making with formal government recognition that provides legitimacy to exclude outsiders and enforcement capacity at larger

The screenshot shows the Elicit.com platform's user interface. On the left, there's a sidebar with a search bar and a 'New' button. The main area has a title 'Status' with three items: 'Gather sources' (60 sources found), 'Screen sources' (10 sources included), and 'Extract data' (60 data points extracted). Below these are buttons for 'Generate report' and 'Save PDF'. On the right, there's a 'Chat' section with a message input field and a scrollable history.

Map a substantive domain: scite.ai

The screenshot shows the scite.ai interface. At the top, there's a navigation bar with 'scite_' (highlighted in blue), 'Assistant', 'Search', 'Pricing', and a 'More' dropdown. On the right are 'Log In' and 'Sign Up' buttons. A sidebar on the left has icons for 'Ask', 'Search', 'Dashboard', and 'Help'. The main content area has a search bar with 'Ask me another question' and a blue 'Ask' button. Below it is a question card: 'What effect does leadership decapitation have on civilian attitudes during conflict?'. To the left of the question is a small icon with a question mark and a counter '1 free prompt(s) left'. Below the question is a link to 'Start your free trial'. The main text of the card discusses the nuanced effects of leadership decapitation on civilian attitudes, mentioning military strategy, political legitimacy, and perceptions of violence. It notes that while it eliminates key figures, it can lead to unintended consequences like increased violence. A quote from Eastin et al. follows, discussing how leadership decapitation can disrupt militant groups' organization and potentially lead to conflict cessation. Another quote from Vasseur et al. discusses the variability of leadership decapitation's effectiveness in achieving insurgent defeat. On the right side of the card, there are sections for 'References' (with a 'Copy' button) and 'Add references to dashboard'. Below the card, there's a section titled 'Targeting Quality or Quantity? The Divergent Effects of Targeting Upper Versus Lower-Tier Leaders of Militant Organizations' by Amira Jadoon¹, Andrew Mines², D. J. Milton³ (2022). It includes a snippet of the text and links to the journal and publisher. At the bottom, there are buttons for 'Dashboard', 'Get access via publisher', and 'Cite' (with a citation count of 66).

Ask me another question

Ask

References

Search Strategy

Copy

Add references to dashboard

What effect does leadership decapitation have on civilian attitudes during conflict?

1 free prompt(s) left. [Start your free trial](#) to get unlimited access.

The effect of leadership decapitation on civilian attitudes during conflicts is a nuanced issue that intertwines military strategy, political legitimacy, and civilian perceptions of violence. Leadership decapitation generally involves eliminating key figures within an insurgency or militant organization, with the intent of destabilizing those groups and ultimately reducing violence. However, the outcomes of such strategies can lead to unintended consequences that affect civilian attitudes, either positively or negatively.

One critical aspect is the alteration in control that follows the removal of leaders. When prominent leaders are eliminated, as noted by Jadoon et al., this can exacerbate the principal-agent problems within militant organizations. The diminished capacity for remaining leaders to exert control often leads to increased violence against civilians as factions vie for power or act without sufficient guidance. This situation can foster a perception of instability and insecurity among civilians, who may feel more threatened by the increased violence than by the original conditions imposed by the insurgent leaders (Jadoon et al., 2022).

Conversely, some studies indicate that leadership decapitation can lead to reductions in violence against civilians under specific circumstances. For example, Eastin et al. discuss how the removal of leadership can disrupt militant groups' organization, potentially paving the way for governmental victory and conflict cessation, which may ultimately result in a more stable environment for civilian populations. Such an outcome can enhance public support for the government or the group conducting the decapitation, as people may view it as a necessary action for restoring peace (Eastin et al., 2023).

Moreover, the effectiveness of leadership decapitation can vary significantly depending on the context and the nature of the insurgency. As highlighted by Vasseur et al., while leadership decapitation can contribute to insurgent defeat, it has a success rate of only approximately 25% to 30% (Vasseur et al., 2022). This variability can affect civilian perceptions; if groups remain resilient despite decapitation, civilians may grow disillusioned with the effectiveness of governmental strategies, potentially leading to reduced support for counterinsurgency efforts.

Targeting Quality or Quantity? The Divergent Effects of Targeting Upper Verses Lower-Tier Leaders of Militant Organizations

Amira Jadoon¹, Andrew Mines², D. J. Milton³ 2022
Journal of Conflict Resolution

2 0 2 0

...In the context of terrorist and insurgent groups, the principal-agent problem is commonly observed where the principals of a ...

Section: Leadership Delegation: Why Lower-level Leaders Matter

Dashboard Get access via publisher

Cite

Map a substantive domain: Keenious.com

The screenshot shows the Keenious.com homepage. At the top, there is a navigation bar with links for Company, Keenious for, Universities, Resources, Pricing, Sign In, and a purple "Get Keenious!" button. Below the navigation is a large, semi-transparent circular graphic containing a search bar with the placeholder "What are you curious about?". The text "Supporting your research journey" and "From discovery to understanding, with AI support along the way" is displayed above the search bar. At the bottom, the text "Universities that trust Keenious include:" is followed by logos for Caltech, Carnegie Mellon University, and the University of Helsinki.

keenious

Company Keenious for Universities Resources Pricing

Sign In Get Keenious!

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Caltech Carnegie Mellon University HELSINGIN YLIOPISTO HELSINGFORS UNIVERSITET UNIVERSITY OF HELSINKI

Map a substantive domain: undermind.ai

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Condense weeks of research to minutes

An AI assistant that carefully explores the scientific literature for you. Find exactly what you need, no matter how complex.

[Try now](#)[Learn more](#)[Experimental evidence of phonon-...](#)[Computational models of hippoco...](#)[Laboratory experiments simulating...](#)

Trusted and used by researchers at



Map a substantive domain: NotebookLM

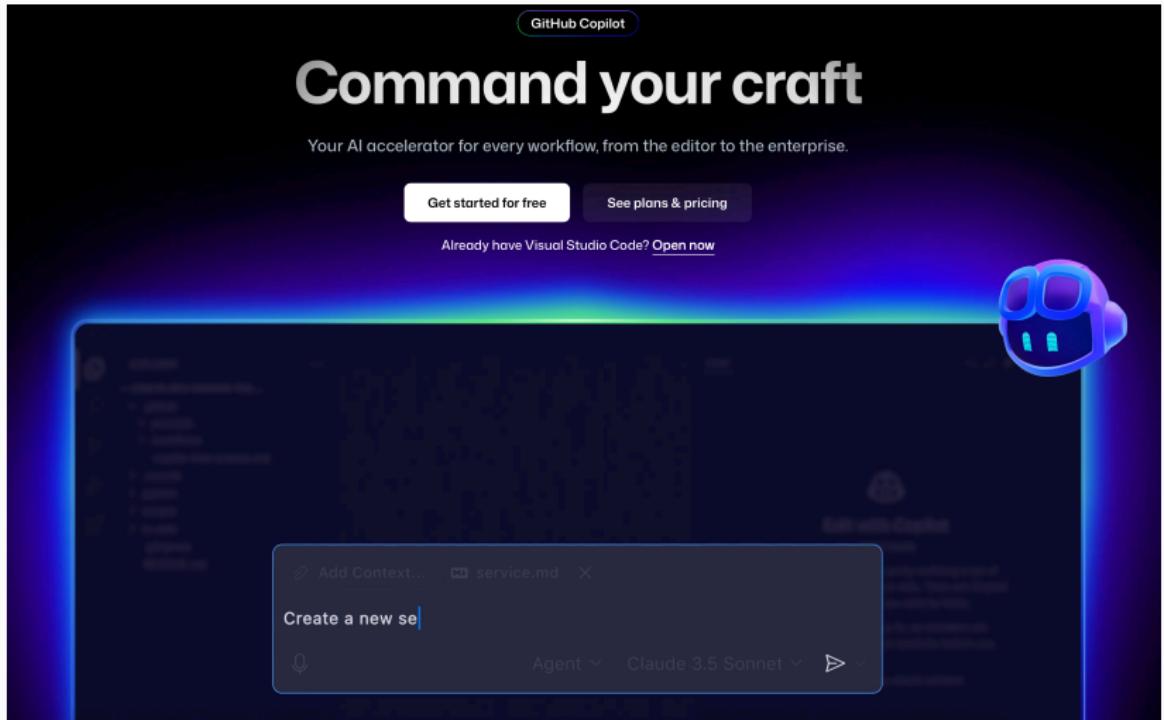
The screenshot shows the homepage of NotebookLM. At the top left is the logo "NotebookLM" with a Wi-Fi icon. At the top right are links for "Overview", "Plans", and social media icons for GitHub, LinkedIn, and X. A button labeled "Get the app" is also present. The main title "Understand Anything" is displayed prominently, with "Anything" in a blue font. Below the title is a subtitle: "Your research and thinking partner, grounded in the information you trust, built with the latest Gemini models." A large "Try NotebookLM" button is centered below the subtitle. The background features a dark green gradient. On the left side, there's a section titled "Upload your sources" with a file icon and a description: "Upload PDFs, websites, YouTube videos, audio files, Google Docs, Google Slides and more, and". On the right side, there's a dark rectangular area with a dashed white rectangle containing a blue circular icon with a plus sign and the text "Upload sources". At the bottom of this area, there's some small, illegible text.

Upload your sources

Upload PDFs, websites, YouTube videos, audio files, Google Docs, Google Slides and more, and

Upload sources

Programming Assistance: Copilot



Leveraging LLMs: Building a ROCKIT Prompt

- R — Role

Tell the model to embrace a persona: You are an expert academic writing coach...

Leveraging LLMs: Building a ROCKIT Prompt

- R — Role

Tell the model to embrace a persona: You are an expert academic writing coach...

- O — Objective

State the single main goal: ...Your task is to generate an abstract for this manuscript.

Leveraging LLMs: Building a ROCKIT Prompt

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- C — Context & Constraints

Give background and rules: Political science journal, technical audience, max 150 words.

Leveraging LLMs: Building a ROCKIT Prompt

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Tell the model to embrace a persona: You are an expert academic writing coach...

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Specify the structure. Leverage recent abstracts in the Journal of Politics and the American Political Science Review as a template.

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You are an expert academic writing coach. Your task is to generate an abstract for this manuscript. Political science journal, technical audience, max 150 words. Include the research question, hypothesis, research design, main finding. Leverage recent abstracts in the Journal of Politics and the American Political Science Review as a template.

Leveraging LLMs: Peer review yourself

Craft a prompt to leverage the model as a ‘reviewer’ of one of your *published* papers. Use a published paper so you can test its ability to identify what you know are interesting/useful/actionable comments.

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You are an accomplished political scientist reviewing a manuscript for publication in the [journal]. Critically evaluate the manuscript for its theoretical argument, research design, and overall clarity. Identify potential weaknesses in the framing, theory, methodology, and implications. Suggest specific ways to improve the manuscript, including its structure and clarity.

Leveraging LLMs: Suggest a Journal

Craft a prompt to leverage the model to suggest an outlet for that paper. You can do this as a follow-up prompt, it has a lot of relevant information in the ‘context’ of your conversation. Task the model with suggesting specific aspects of the paper to adapt or improve to align with the journal, or a targeted journal.

Leveraging LLMs: Ideate an Extension

Craft a prompt to leverage the model to suggest a follow-up study from the same paper. Task the model with outlining what gap the paper would fill, a plausible research design, and whatever else you think would be useful.

Leveraging LLMs: Suggest a Grant

Craft a prompt to leverage the model to suggest a follow-up grant from the same paper. Task the model with searching the internet or using its knowledge to suggest a specific grant that you could apply for using the manuscript. Instruct the model to provide a strategy for winning the award and to consider whatever might be relevant to your specific situation.

Leveraging LLMs: Suggest a Paper

In a fresh session, craft a prompt to summarize the same paper you were working on with the model. How well does it do?

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- Remember that the model will make things up
- It may not accurately copy text, reliably extract information, etc.
- The model can help with formatting citations, rewriting text, etc. but note that it has no guaranteed mapping between input/output and may change the content of the text

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- Suggesting interesting case studies?
- What else?
- Lessons learned?
- Concerns? Ethics?