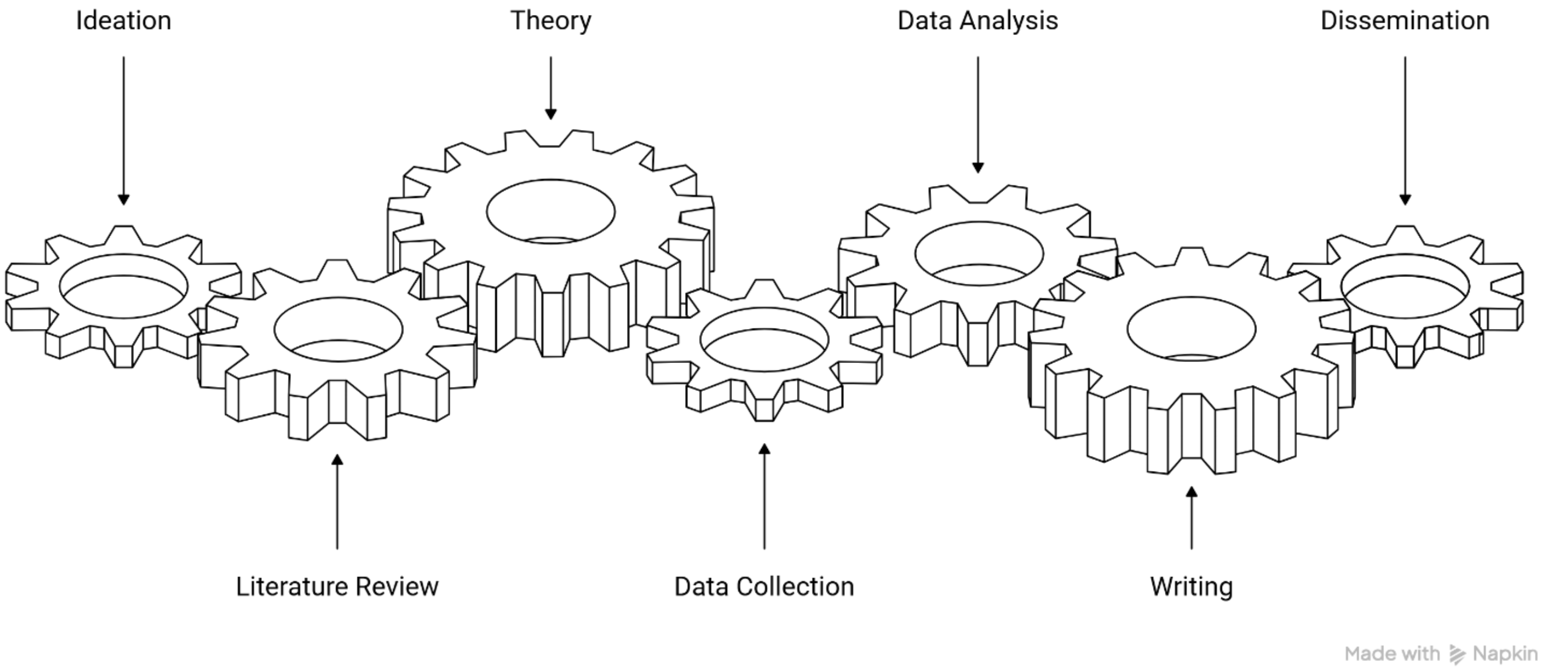
AI Across the Academic Workflow

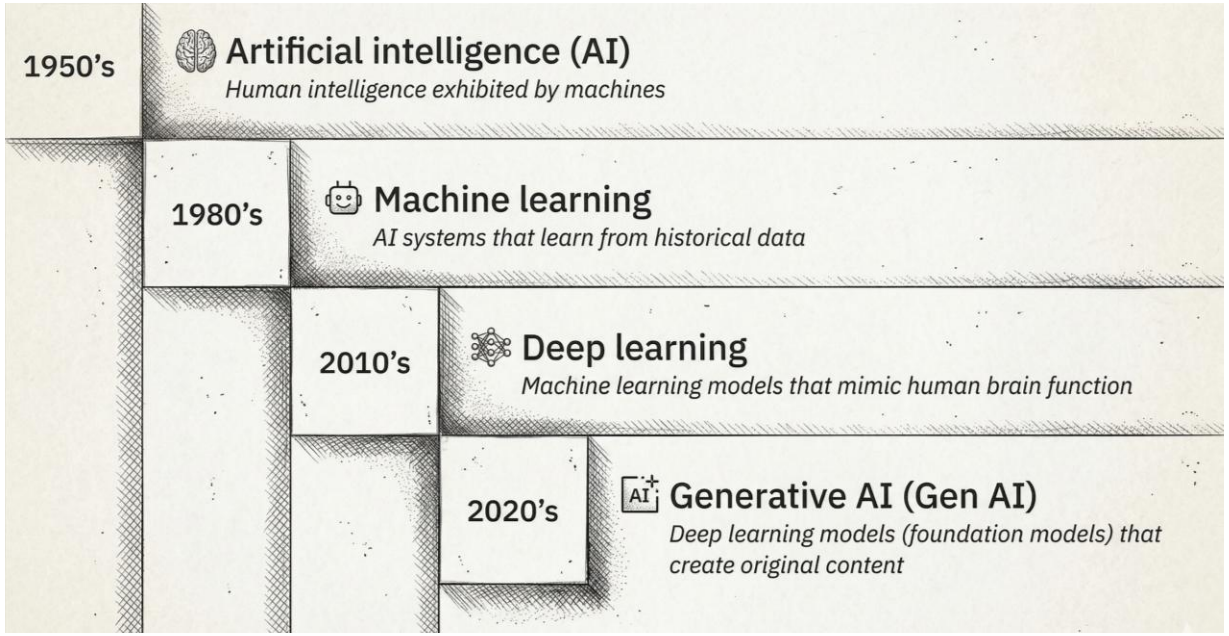
A Pragmatic Look at What's Possible Today



Version: April 9, 2026

What is Artificial Intelligence?

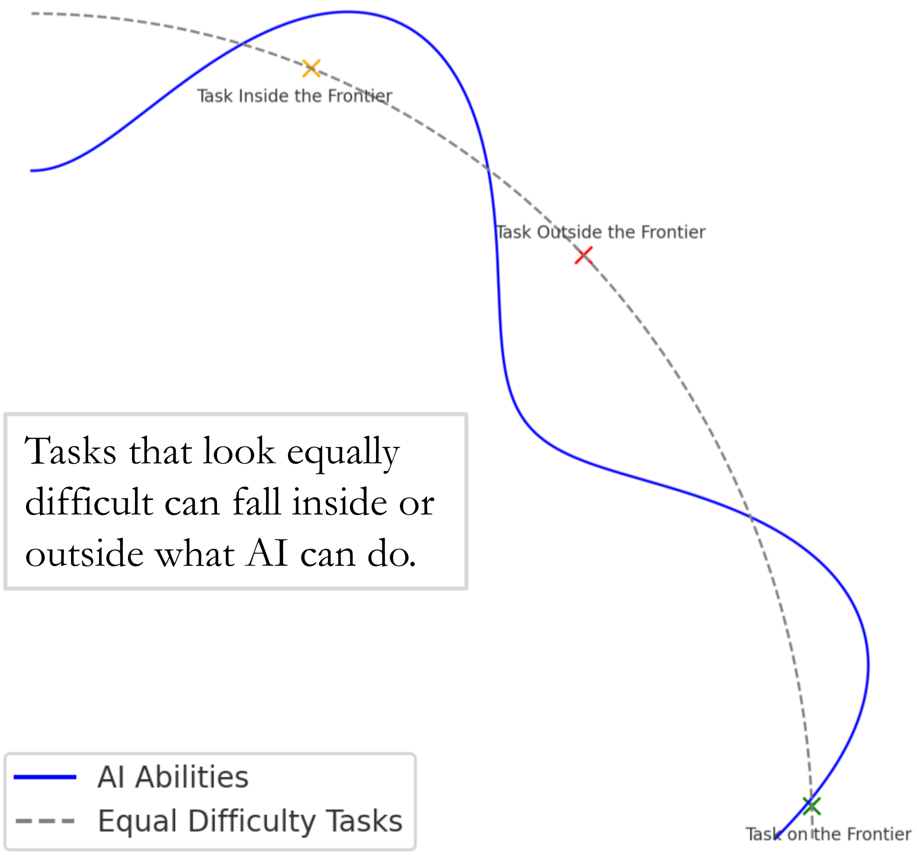
Artificial intelligence (AI) is technology that enables computers and machines to simulate human learning, comprehension, problem-solving, decision-making, creativity, and autonomy. #cognitivetasks



https://www.ibm.com/think/topics/artificial-intelligence

What's All the Fuzz About?

Jagged Frontier of AI Capabilities



Tasks that look equally difficult can fall inside or outside what AI can do.

https://www.oneusefulthing.org/p/centaurs-and-cyborgs-on-the-jagged | No Priors Podcast

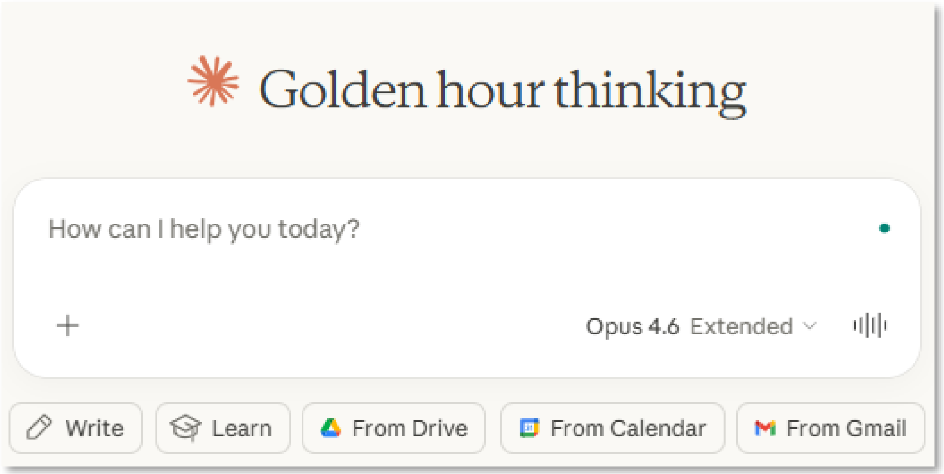
Why *Quantitative* Researchers Embrace AI

- ✅ Strong alignment with positivist research traditions (objective reality)
- ✅ Accelerates tedious, time-consuming tasks across the research workflow
- ✅ Enables tasks that were previously impossible without programming skills

Research shouldn‘t be harder than it needs to be…

Using Generative AI Models *Casually*

(a) Web/app interface



- Hidden system prompts #sycophancy
- Randomness to emulate natural conversations #replicability
- Single calls and responses #scalability
- Spillovers and context rot #reliability

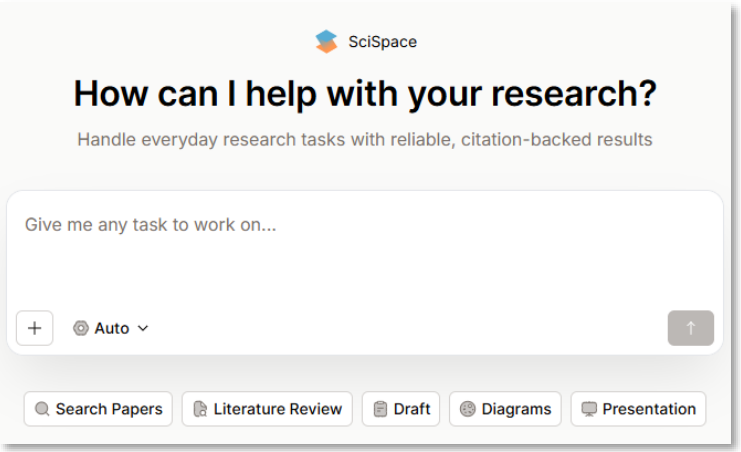
Using Generative AI Models *Professionally*

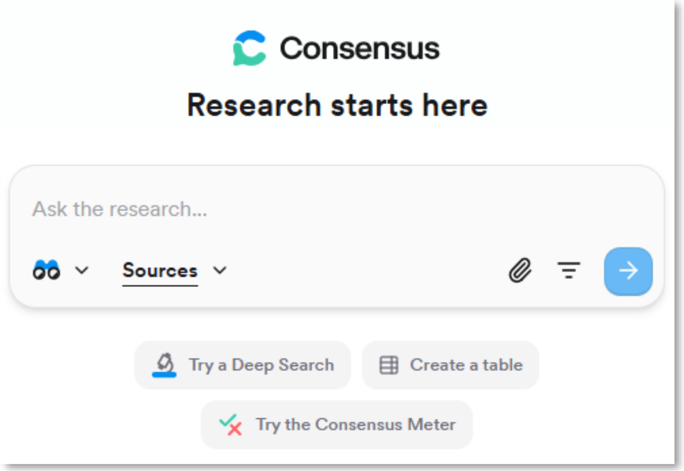
(b) Application programming interface (API)

```
import anthropic

client = anthropic.Anthropic(api_key="your-api-key")

def chat_with_claude(prompt, chat_history=[]):
    chat_history.append({"role": "user", "content": prompt})

    response = client.messages.create(
        model="claude-sonnet-4-20250514",
        max_tokens=1024,
        messages=chat_history
    )

    reply = response.content[0].text
    chat_history.append({"role": "assistant", "content": reply})

    return reply, chat_history

# Example usage
chat_log = []
user_input = "What does API stand for?"
response, chat_log = chat_with_claude(user_input, chat_log)
print("Assistant:", response)
```

- Model selection #replicability
- Custom system prompt #replicability
- Randomness configuration #replicability
- Seed setting #replicability
- Looped calls and responses #scalability
- Context reset #reliability
- Structured output #scalability
- Function calling #scalability

But What About Specialized Tools?





AI Wrappers: Services with tailored user interfaces that *wrap around* existing (non-disclosed) AI models via APIs, using (non-disclosed) custom system prompts and (non-disclosed) external resources (e.g., scholarly databases).

Looking Under the Hood

Distinguish Core Capabilities from User Interface Wrappers

Know Your Models

Chat ⌄ Code Image ⌄ Video ⌄

First Place Second Place Third Place

Default ⌄ Compact View ⌄

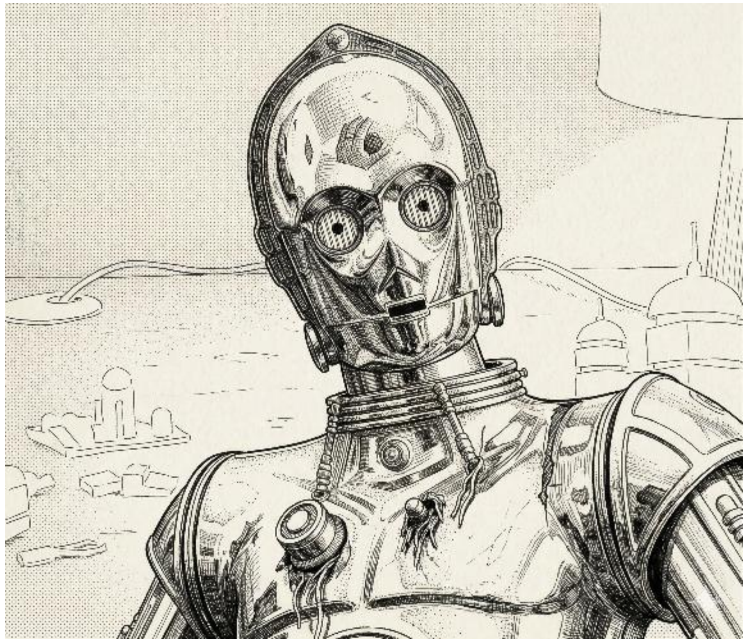
Model ⌄ 632 / 632	Overall	Expert	Hard Prompts	Coding	Math	Creative Writing	Instruction Following	Longer Query
claude-opus-4-6-thi…	1	2	1	1	2	1	1	1
claude-opus-4-6	2	1	2	2	4	6	2	2
gemini-3.1-pro-prev…	3	4	3	4	3	2	3	3
grok-4.20-beta1	4	26	5	6	19	4	10	14
gemini-3-pro	5	10	6	12	5	3	8	7
gpt-5.4-high	6	3	4	3	1	9	4	8
grok-4.20-beta-0309…	7	19	8	9	15	12	14	22
gpt-5.2-chat-latest…	8	21	11	11	21	21	15	19
grok-4.20-multi-age…	9	5	14	7	11	11	26	18
gemini-3-flash	10	14	13	23	7	8	18	15

- Six frontier models in February 2026 alone
- Dramatically improved multi-step reasoning and larger context windows

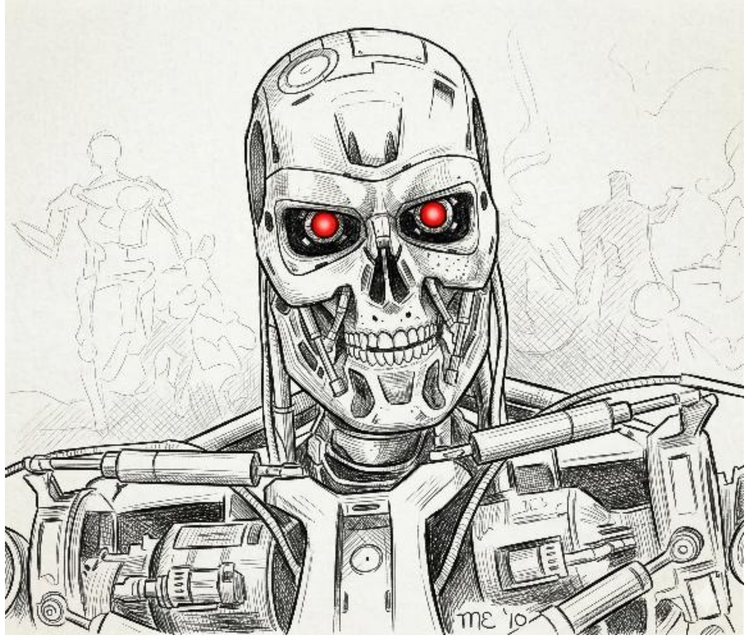
https://lmarena.ai/ | Last Update: April 8, 2026

The Evolution of Generative AI

The Stochastic Parrot



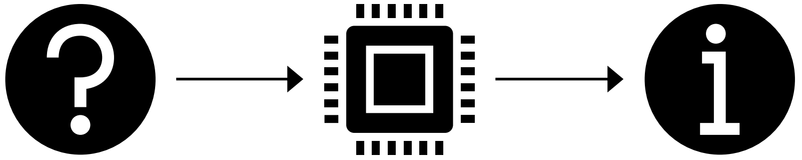
The Useful Co-Pilot

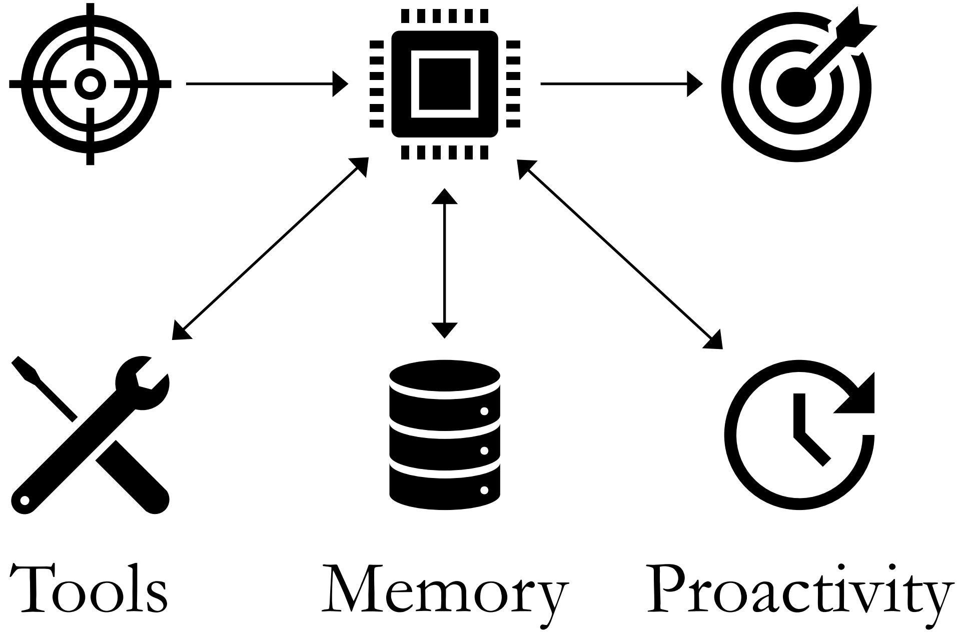


The Autonomous Agent

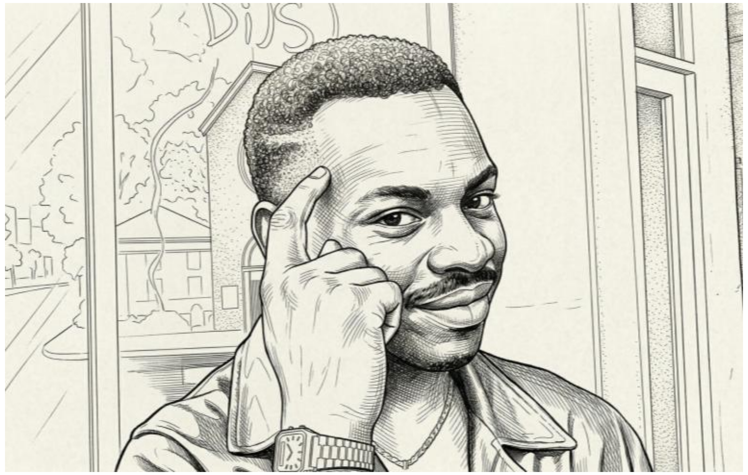
2022 2023 2024 2025 2026

The Shift Towards Agentic AI





The Stages of AI Use



Prompting

- One prompt in, one answer out
- AI with no memory or context
- AI as a smarter search box

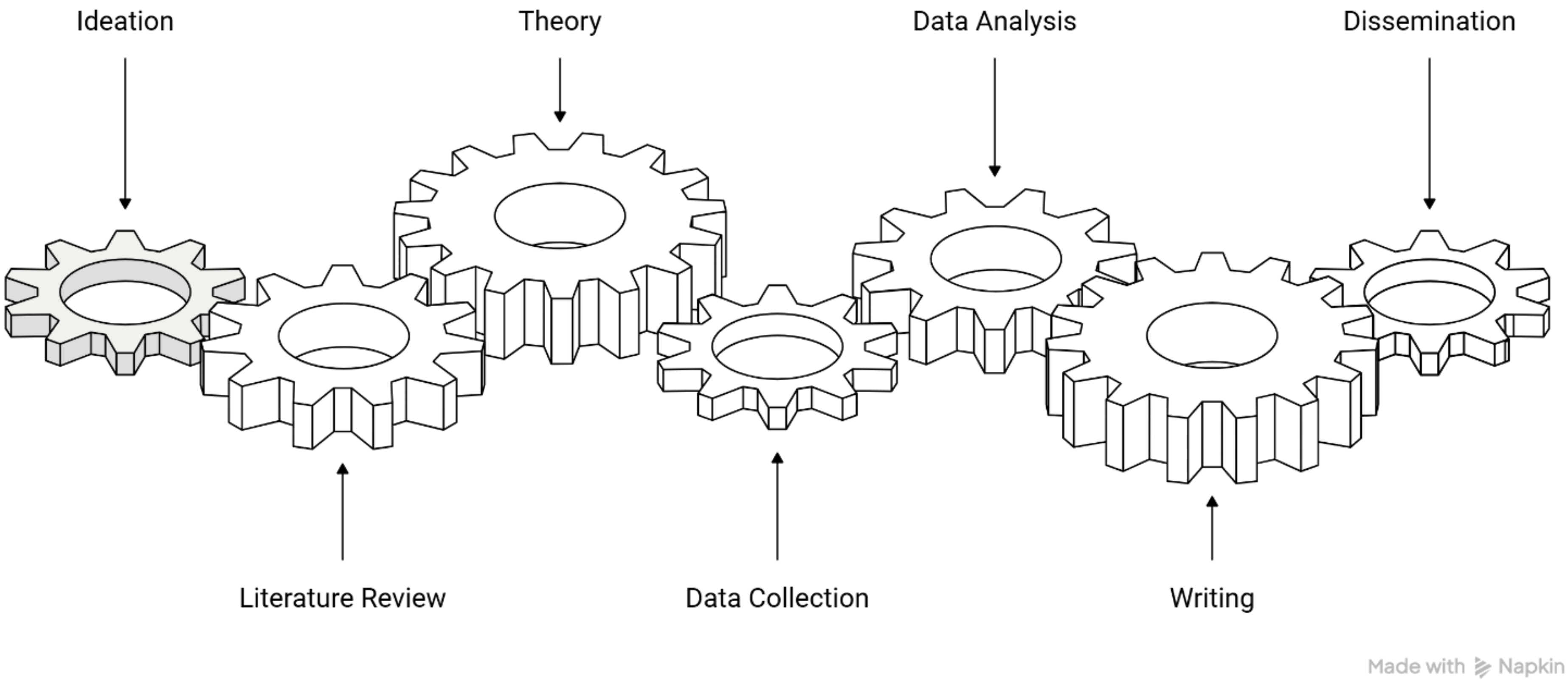
Partnering

- Project-based; you supply context
- AI is one tool among many
- You remain the operator

Delegating

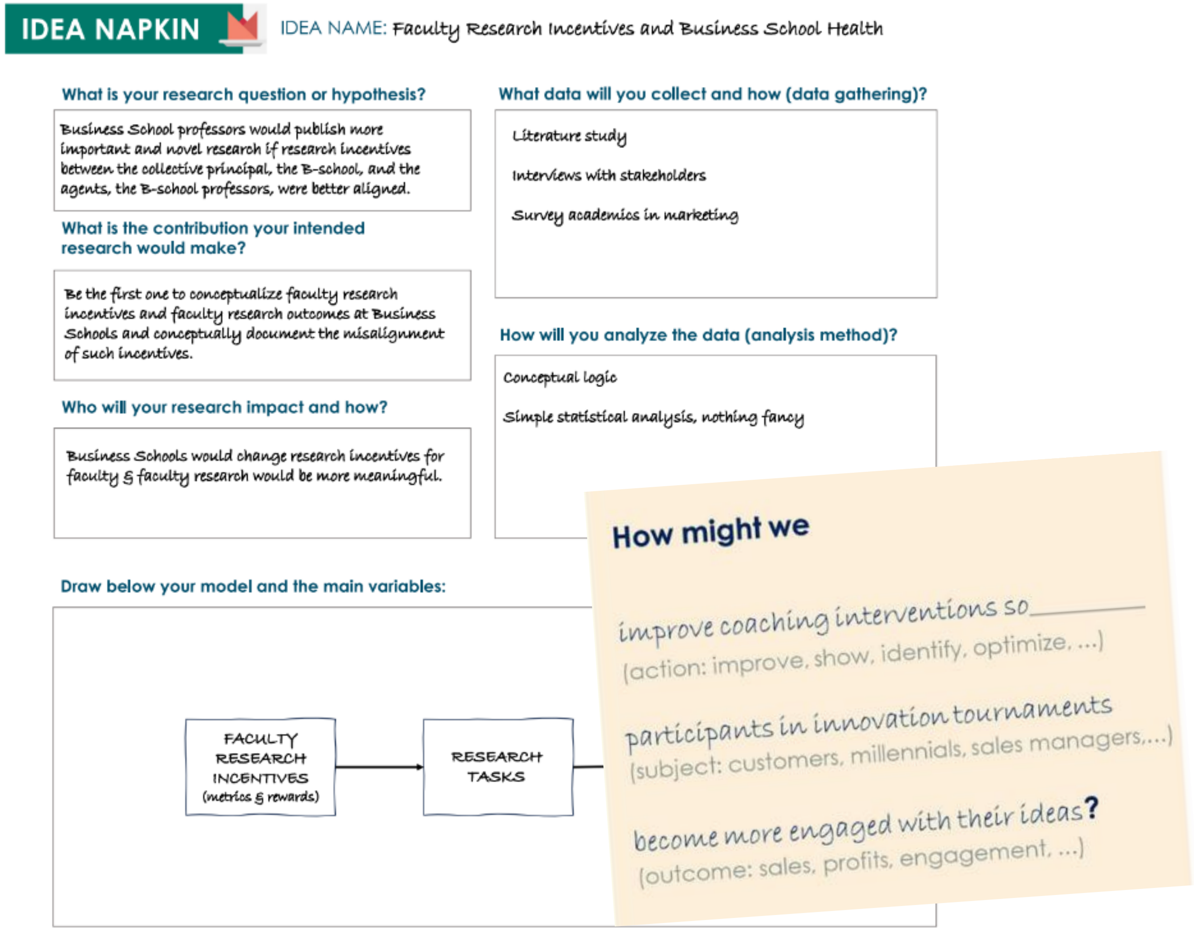
- Fully integrated with your tools and files
- AI executes multi-step tasks end-to-end
- You set goals and supervise

The Academic Workflow



Finding a Needle in a Generated Haystack

- Generate a large number of white horse ideas following a specified format/template
- Output: Ideated abstract
- Manual review
- Soon: Automated review
  - Novelty against the existing literature
  - Predicted interestingness (trained on human judgments)



Gu and Krenn 2025 | Stremersch 2024

Spotting New Trends

- Bird's eye view
- Access to contemporary information (via web access or specific APIs), in addition to pre-trained knowledge
- Deep research functions yield hundreds of sources
- Material can be pooled in a single retrieval-augmented generation (RAG) system like NotebookLM

perplexity

you.com

exa

Gemini Deep Research

Deep research

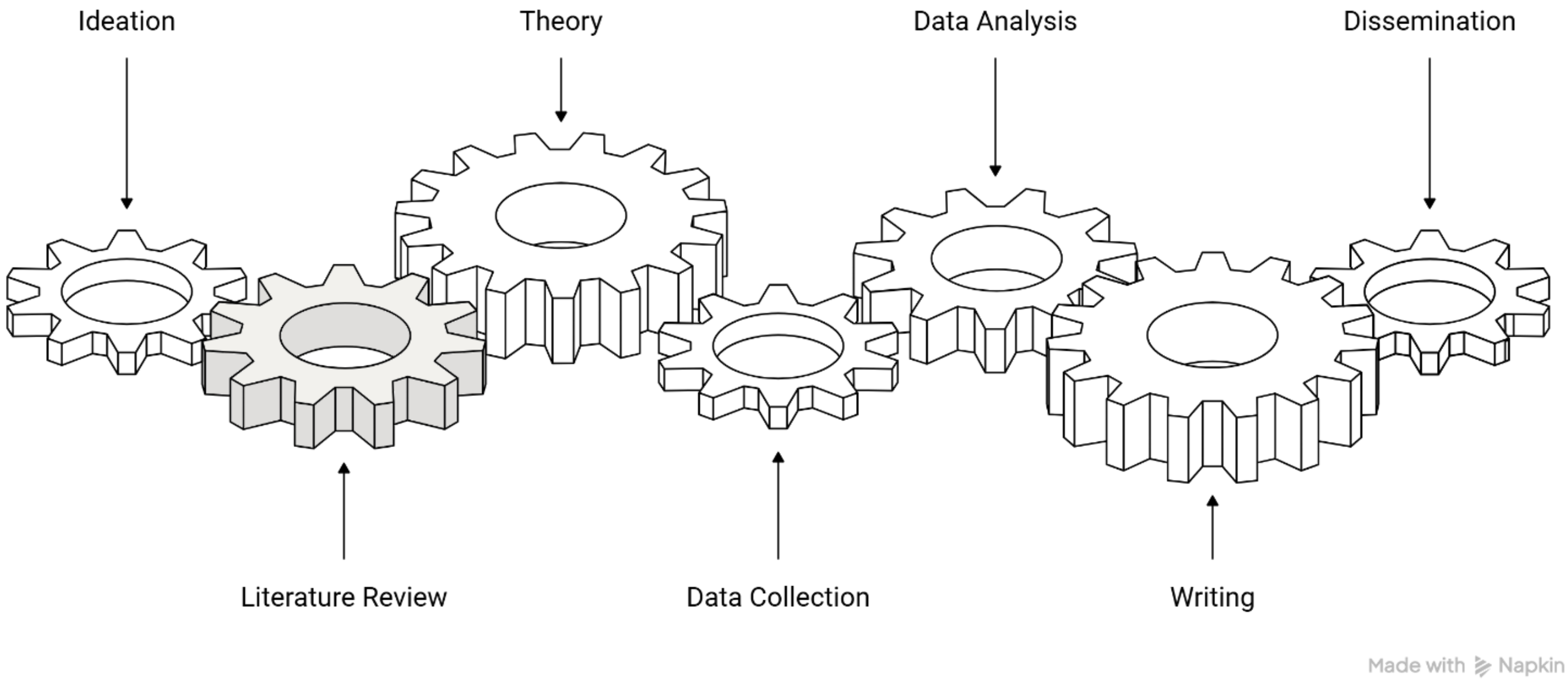
Identify the Diamond in the Rough

Good research must be interesting, compelling, and potentially surprising.

- Gap-spotting (e.g., voids, extensions)
- Problem-identification (e.g., contradictions)
- "Red team" ideas
  - LLMs are cheap, tireless adversaries
  - Use them to attack an idea from every angle before you commit years of time and effort
  - AI agents can be tasked to challenge you (e.g., Research Companion)

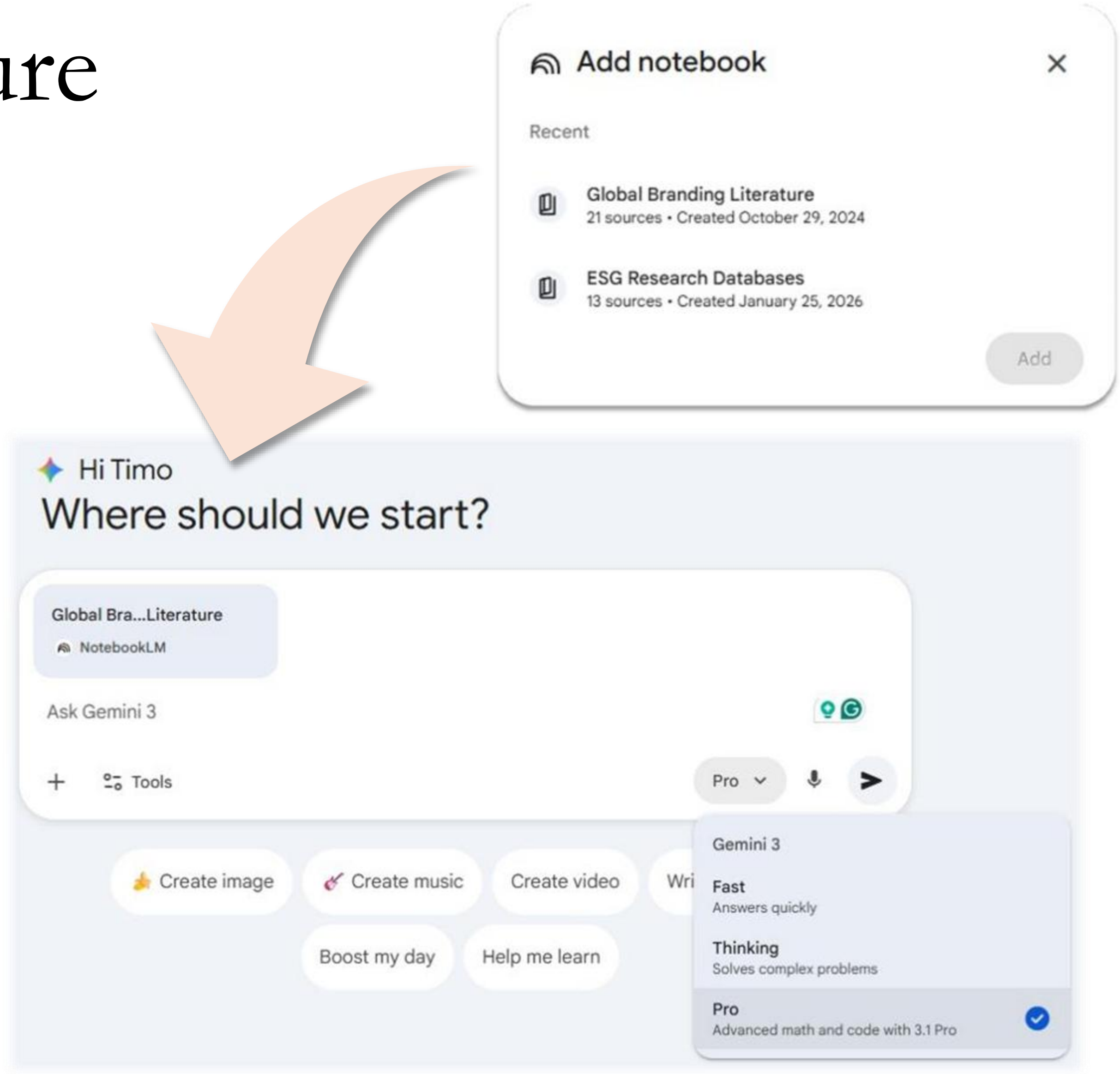
Pillutla and Thau 2013; Sandberg and Alvesson 2011| https://github.com/andrehuang/research-companion/

The Academic Workflow



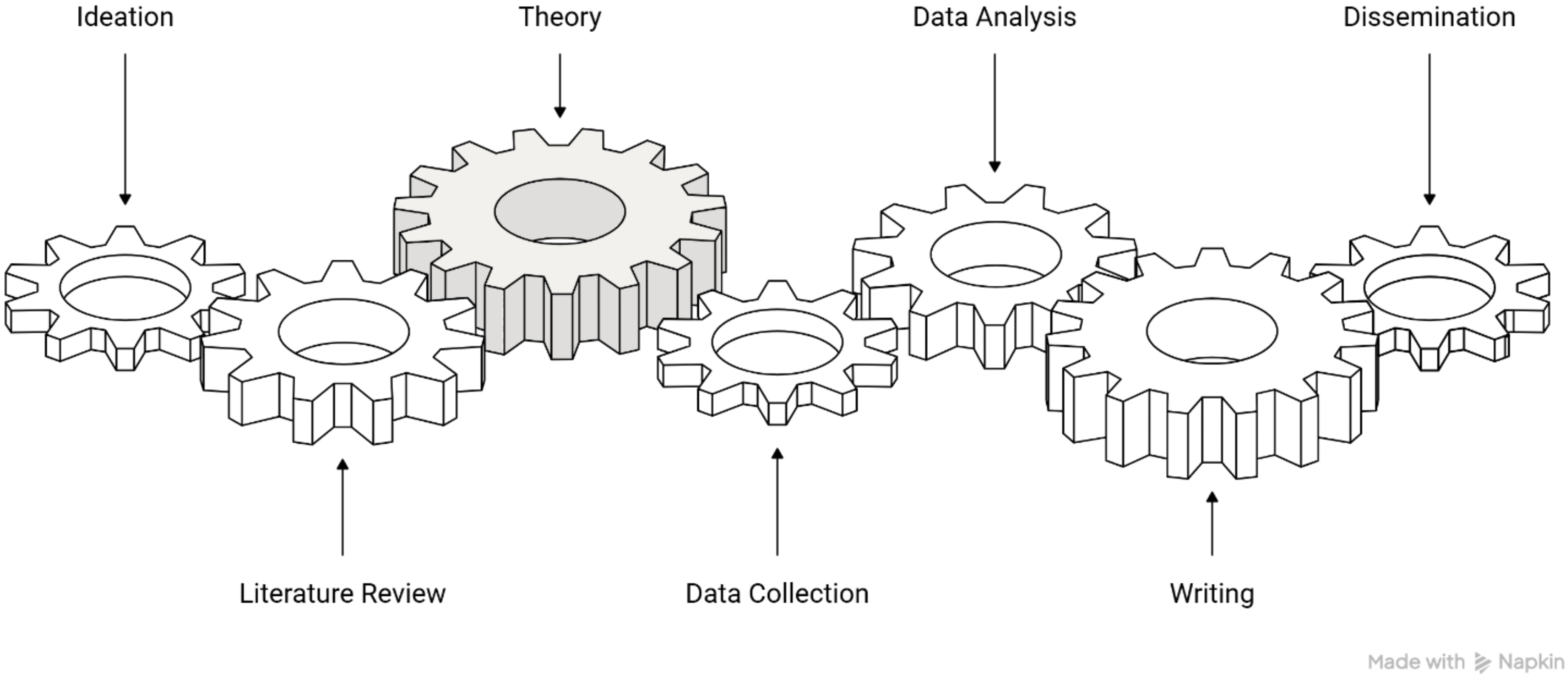
Reviewing the Literature

- Use ready-made tools (e.g., ResearchRabbit, Elicit) for exploration at best
- <u>Remember:</u> AI wrappers suffer from a significant black box problem
- Consider using more transparent RAG systems, such as NotebookLM



https://notebooklm.google.com/

The Academic Workflow



Theory

Depending on the epistemological approach, theoretical explanations may be developed **deductively** by formulating hypotheses in advance or **inductively** by interpreting the empirical evidence post hoc.

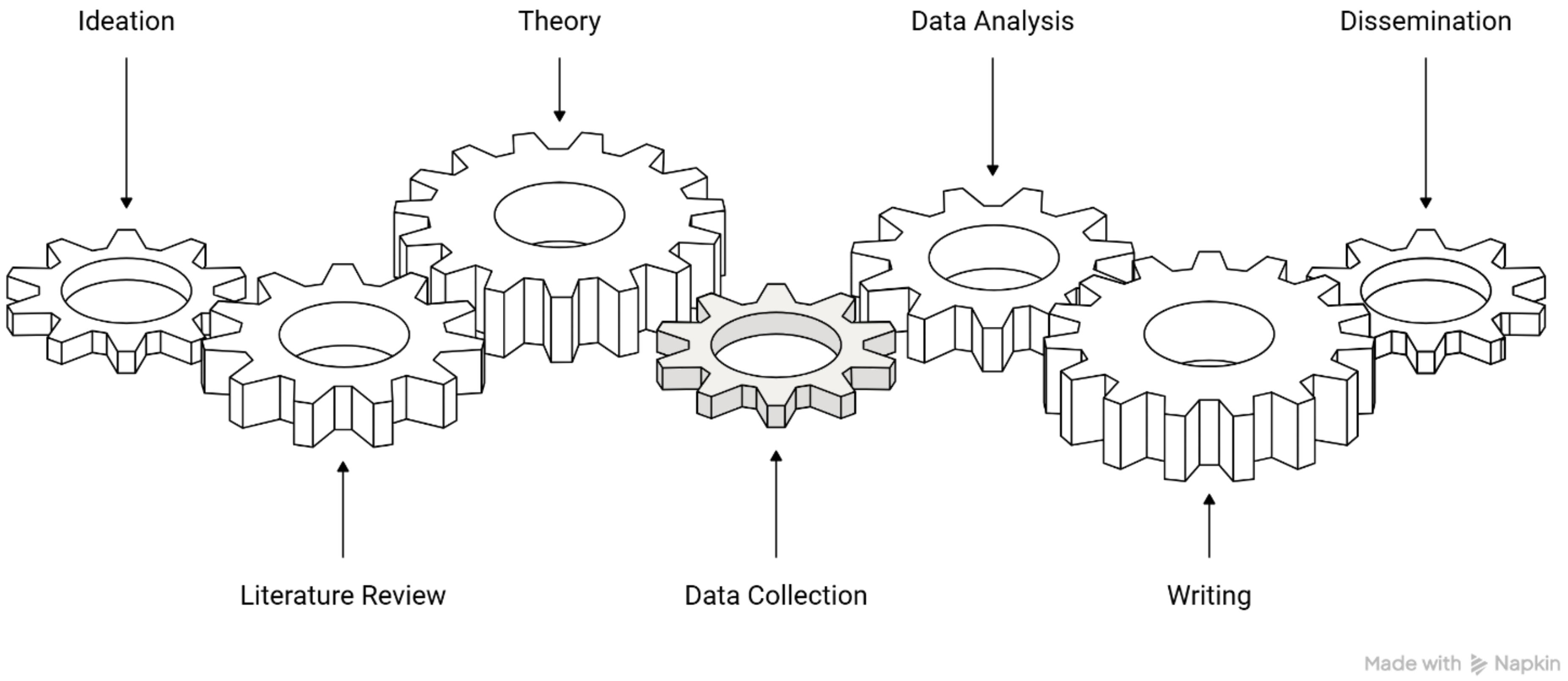
Via prompting

- Mediators (causal mechanisms)
- Moderators (catalysts, inhibitors, boundary conditions)
- Important: Provide sufficient context (e.g., framework)

Via simulation

- Synthetic participants with latent human characteristics
- Inference of potential mediators and moderators
- Useful to probe external validity

The Academic Workflow



Collecting Data for Your Research

Primary data

- Generating synthetic respondents
- Facilitating human-AI interactions

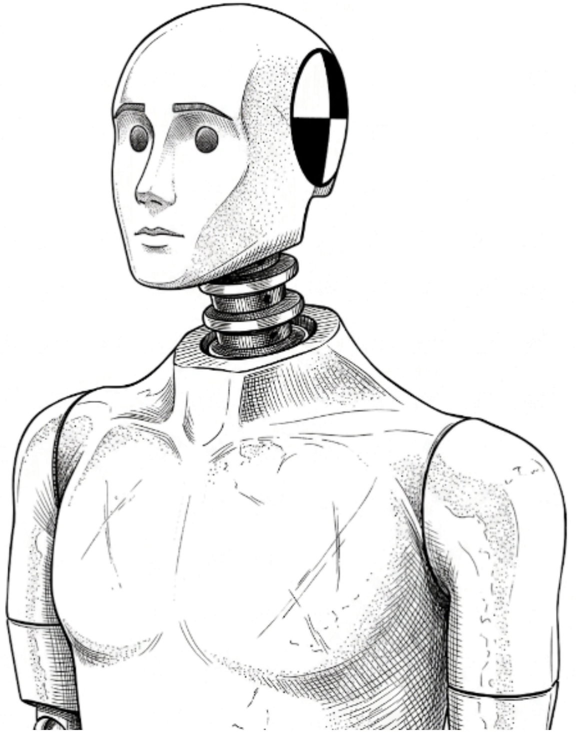
Secondary data

- Scraping websites
- Accessing data through APIs
- Leveraging search capabilities

Generating Synthetic Respondents

- Synthetic respondents (also "AI Personas") with latent human characteristics

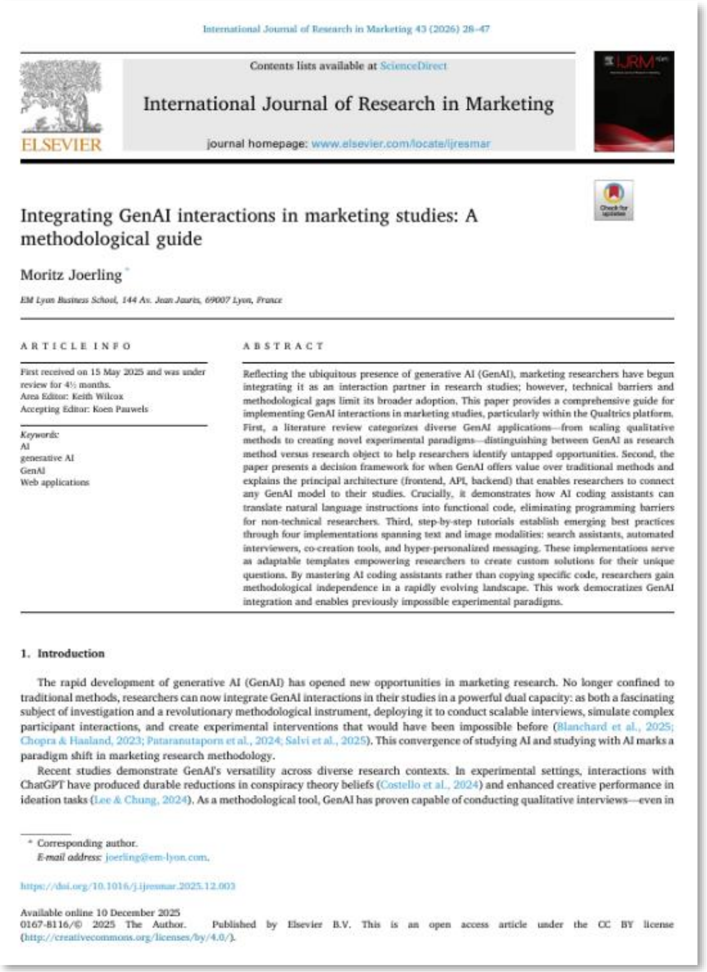
Type	Prompt
Context	You are a respondent on a survey involving pet foods and today is August 19, 2019. Furthermore, • A premium, fresh pet food shown below can be found in a fridge within your local store that carries pet food. • This refrigerated pet food is made with real, high-quality ingredients. It is available in both a resealable bag containing bite-size chunks and pieces or in a sliceable roll in a plastic wrap.
System	Pretend that: • You currently own a dog. • You are likely to purchase refrigerated fresh dog food in the future assuming that. • It is available where you shop for pet food and offered at a reasonable price. Here are some of your other descriptive characteristics as a survey respondent: • You are White or Caucasian, male and 77 years old. • You live in the west region in the United States. The area in which you live is rural. • Your household has 2 people. Your marital status is married. • Your education level is some college and your annual household income is 115,000 U.S. dollars. • Your employment status is retired.
User	A question is typically described to the LLM as follows: • Question: How often would you purchase this refrigerated (fresh) dog food idea? • Answer format: Answer the question with a single number only. Do not include any other information. Use this format to answer: 2 • Choices: (1) Once every 6–11 months, (2) Less than once a year, (3) Once every 2–3 months, (4) Once a year, (5) Multiple times per week, (6) Once every 4–6 months, (7) 2–3 times per month, (8) Once a month, (9) Once a week.



Arora, Chakraborty, and Nishimura 2024 | Exemplary implementation (using Viewpoints AI): Yeykelis et al. 2025

Facilitating Human-AI Interactions

- Modern survey tools (e.g., Qualtrics) can interact with APIs (through JavaScript)
- Enabling dynamic interactions between respondents and an LLM
- Chatbot customizable (e.g., goal, tone)
- Conversations stored as embedded data
- High external validity (vs. scenarios)
- <u>But:</u> New analytical challenges



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Integrating GenAI interactions in marketing studies: A methodological guide

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ABSTRACT

Reflecting the ubiquitous presence of generative AI (GenAI), marketing researchers have begun integrating it as an interaction partner in research studies; however, technical barriers and methodological gaps limit its broader adoption. This paper provides a comprehensive guide for implementing GenAI interactions in marketing studies, particularly within the Qualtrics platform. First, a literature review categorizes diverse GenAI applications—from scaling qualitative methods to creating novel experimental paradigms—distinguishing between GenAI as research method versus research object to help researchers identify untapped opportunities. Second, the paper presents a decision framework for when GenAI offers value over traditional methods and explains the principal architecture (frontend, API, backend) that enables researchers to connect any GenAI model to their studies. Crucially, it demonstrates how AI coding assistants can translate natural language instructions into functional code, eliminating programming barriers for non-technical researchers. Third, step-by-step tutorials establish emerging best practices through four implementations spanning text and image modalities: search assistants, automated interviewers, co-creation tools, and hyper-personalized messaging. These implementations serve as adaptable templates empowering researchers to create custom solutions for their unique questions. By mastering AI coding assistants rather than copying specific code, researchers gain methodological independence in a rapidly evolving landscape. This work democratizes GenAI integration and enables previously impossible experimental paradigms.

1. Introduction

The rapid development of generative AI (GenAI) has opened new opportunities in marketing research. No longer confined to traditional methods, researchers can now integrate GenAI interactions in their studies in a powerful dual capacity: as both a fascinating subject of investigation and a revolutionary methodological instrument, deploying it to conduct scalable interviews, simulate complex participant interactions, and create experimental interventions that would have been impossible before (Blanchard et al., 2025; Chopra & Haaland, 2023; Pataranutaporn et al., 2024; Salvi et al., 2025). This convergence of studying AI and studying with AI marks a paradigm shift in marketing research methodology.

Recent studies demonstrate GenAI's versatility across diverse research contexts. In experimental settings, interactions with ChatGPT have produced durable reductions in conspiracy theory beliefs (Costello et al., 2024) and enhanced creative performance in ideation tasks (Lee & Chung, 2024). As a methodological tool, GenAI has proven capable of conducting qualitative interviews—even in

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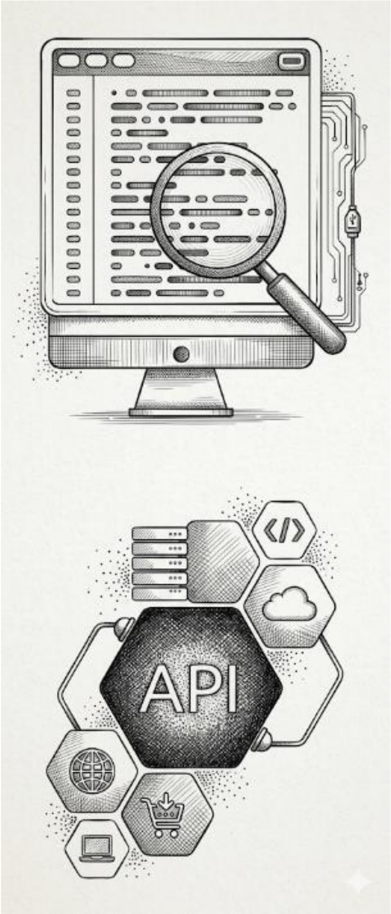
Available online 10 December 2025

Scraping Websites and Accessing APIs



- Provide source code or API documentation (e.g., WRDS)
- Explain particularities and provide examples
- Specify how the data should be recorded
- Specify preferred programming language (and packages)
- Revise the script iteratively until the output meets your expectations (start with a subset for testing)

Agentic AI rapidly collapses these steps, turning scraping from a **scripting task** into a **supervision task**.

“Scanning” the Web with Search Capabilities

- Gathering of unstructured data from various (non-predetermined) sources (vs. gathering data from specific, predetermined sources)
- Post-processing with an LLM to obtain a structured output

Send (looped) requests

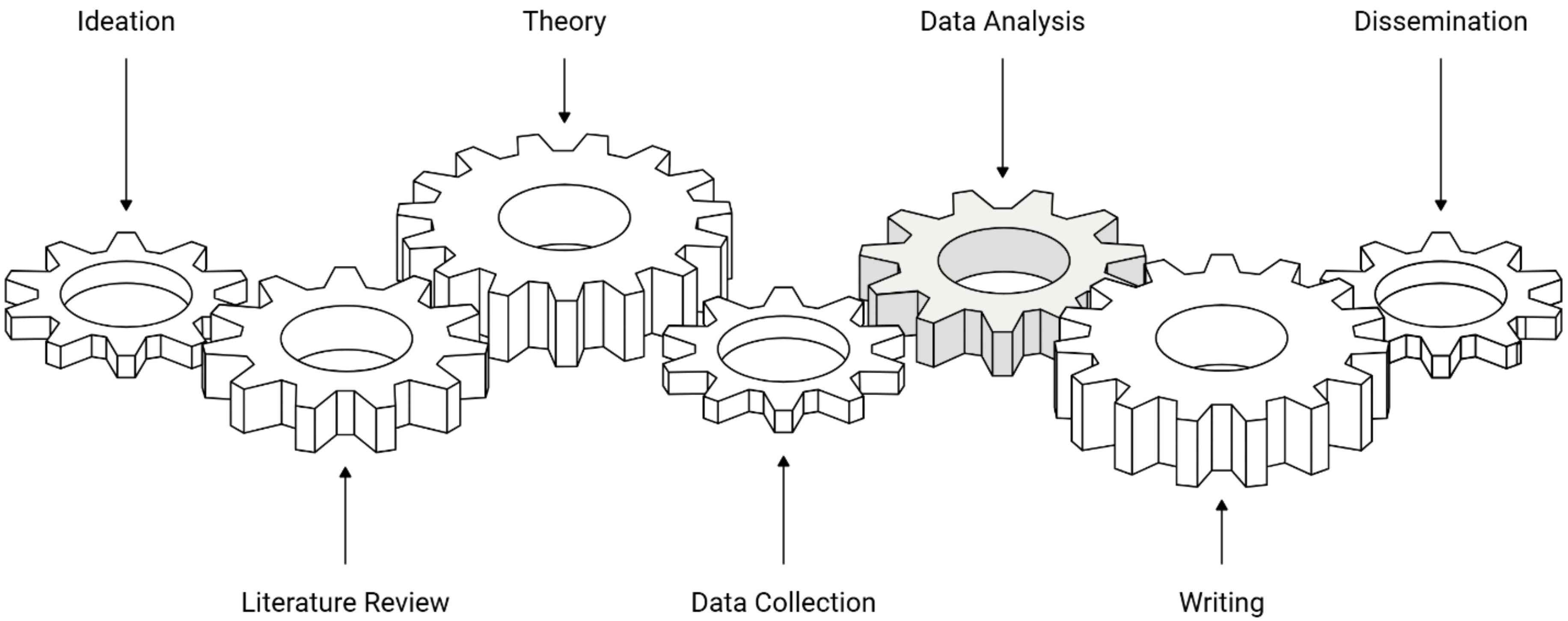
Store search results

Extract and classify information

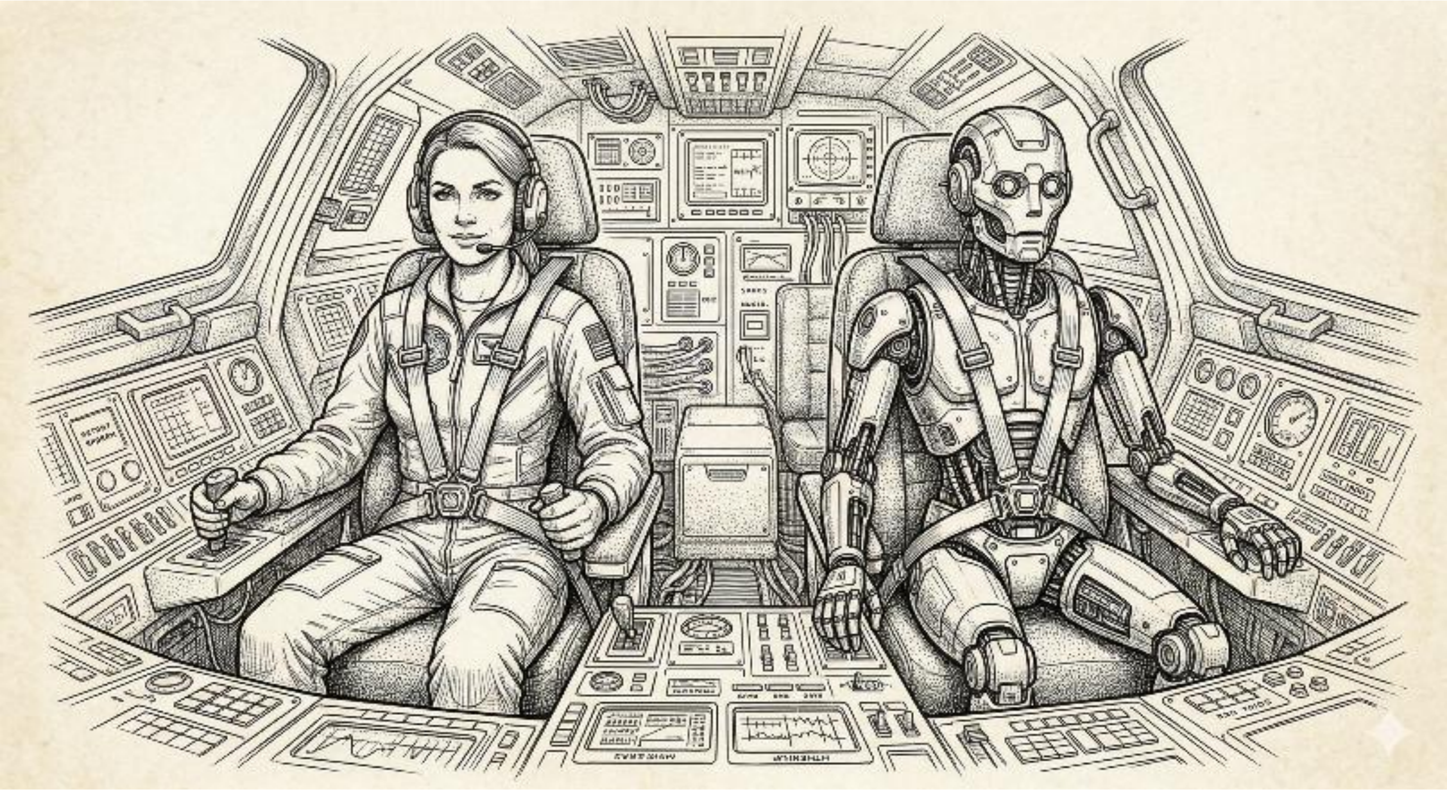
brand	search_result	reliability	lower_l	upper_	qualifie	source	year
1&1	VERIFIED: 1&1 in	VERIFIED	1		exactly	1&1 Annua	2024
23andMe	VERIFIED: Accord	VERIFIED	47		exactly	23andMe (	2025
A & P	VERIFIED: The bra	VERIFIED	2		exactly	Wikipedia	2015
ADAC Versicherungen	VERIFIED: ADAC V	VERIFIED	1		exactly	DitchCarb	2025
AGL Energy	VERIFIED: AGL En	VERIFIED	1		exactly	AGL Officia	2024
AIA	VERIFIED: AIA Gro	VERIFIED	18		exactly	AIA Group	2020
AMC	VERIFIED: AMC (a	VERIFIED	130		more thar	AMC Netw	2025
AMP (Finance)	CREDIBLE ESTIMA	VERIFIED	2		exactly	GlobalDat	2025
AP Pension	VERIFIED: AP Pen	VERIFIED	1		exactly	AP Pensio	2024
AXA	VERIFIED: AXA's i	VERIFIED	51		exactly	AXA's offic	2025
Aarstiderne	VERIFIED: Aarstic	VERIFIED	2		exactly	Rubizmo,	2024
AbbVie	CREDIBLE ESTIMA	VERIFIED	70		more thar	AbbVieâ€	2024
Abbott	CREDIBLE ESTIMA	VERIFIED	160		over	abbott.coi	2025
Accor	VERIFIED: Accor,	VERIFIED	110		over	Official Ac	2025
Acer	VERIFIED: Accord	VERIFIED	160		more thar	Acer Grou	2024
Action	VERIFIED: As of Ju	VERIFIED	14		exactly	Action (sto	2025
Activision	VERIFIED: Activis	VERIFIED	196		exactly	Activision	2024
Acura	VERIFIED: Acura I	VERIFIED	4	5	between	Statista (A	2024
Adidas	VERIFIED: Adidas	VERIFIED	160		more thar	Adidas US	2025

Mandler et al. 2026 (unpublished manuscript)

The Academic Workflow



LLMs as a Co-Pilot (Not Auto-Pilot)



A co-pilot does not replace a pilot's training.

Leapfrog Traditional Text Analysis Methods

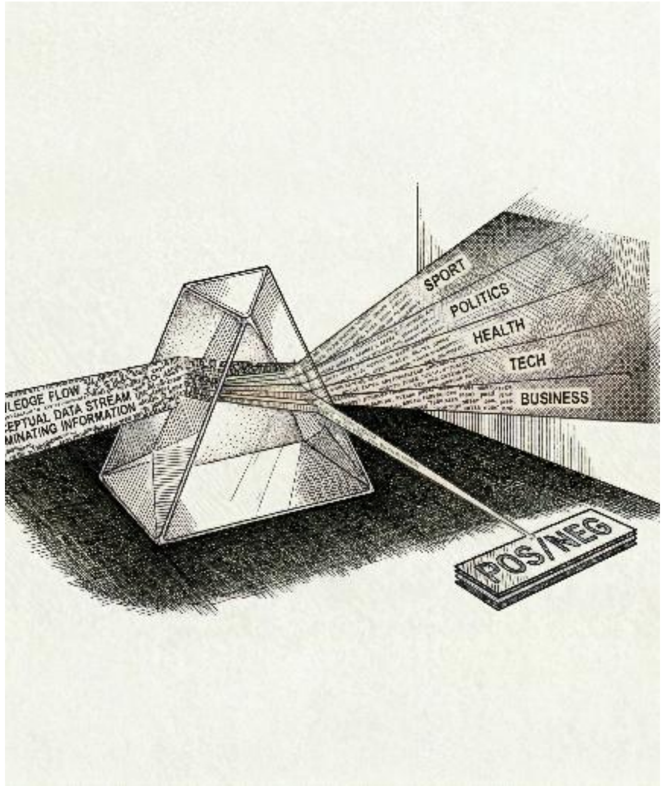
- **Dictionaries:** Counting or scoring words that represent a construct
- **Topic models:** Identification of latent topics in a dataset
- **Supervised ML and DL:** Prediction of a class based on text
- **Embeddings:** Examine relationships between words and concepts

LLMs can be seen as an alternative to each of these traditional methods:
Create context-aware dictionaries ✓ Apply topic models ✓
Predict outcomes based on text ✓ Use embeddings to map associations ✓

Villarroel Ordenes et al. 2025

LLMs Outperform Traditional Methods

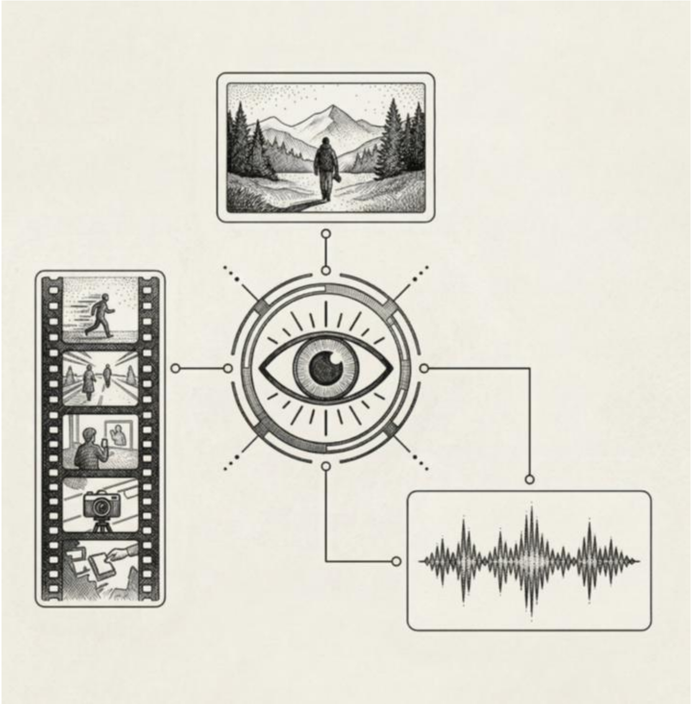
- GPT-4 outperforms all other NLP **classification approaches** (dictionaries, topic modeling, word embeddings, transformers)
- GPT-4 exhibits a remarkable zero-shot **sentiment analysis** performance, on par or even exceeding (fine-tuned) transformer models (e.g., RoBERTa, XLNet)
- GPT-3.5 Turbo outperforms crowd workers (MTurk Masters) for **annotation tasks**
- **GABRIEL**'s (OpenAI × Harvard University) classification and attribute rating performance is indistinguishable from human evaluators



Asirvatham, Mokski, and Shleifer 2026; Gilardi, Alizadeh, and Kubli 2003; Krugmann and Hartmann 2024; Maibaum et al. 2024 | GABRIEL Tutorial: https://tinyurl.com/gabriel-gpt

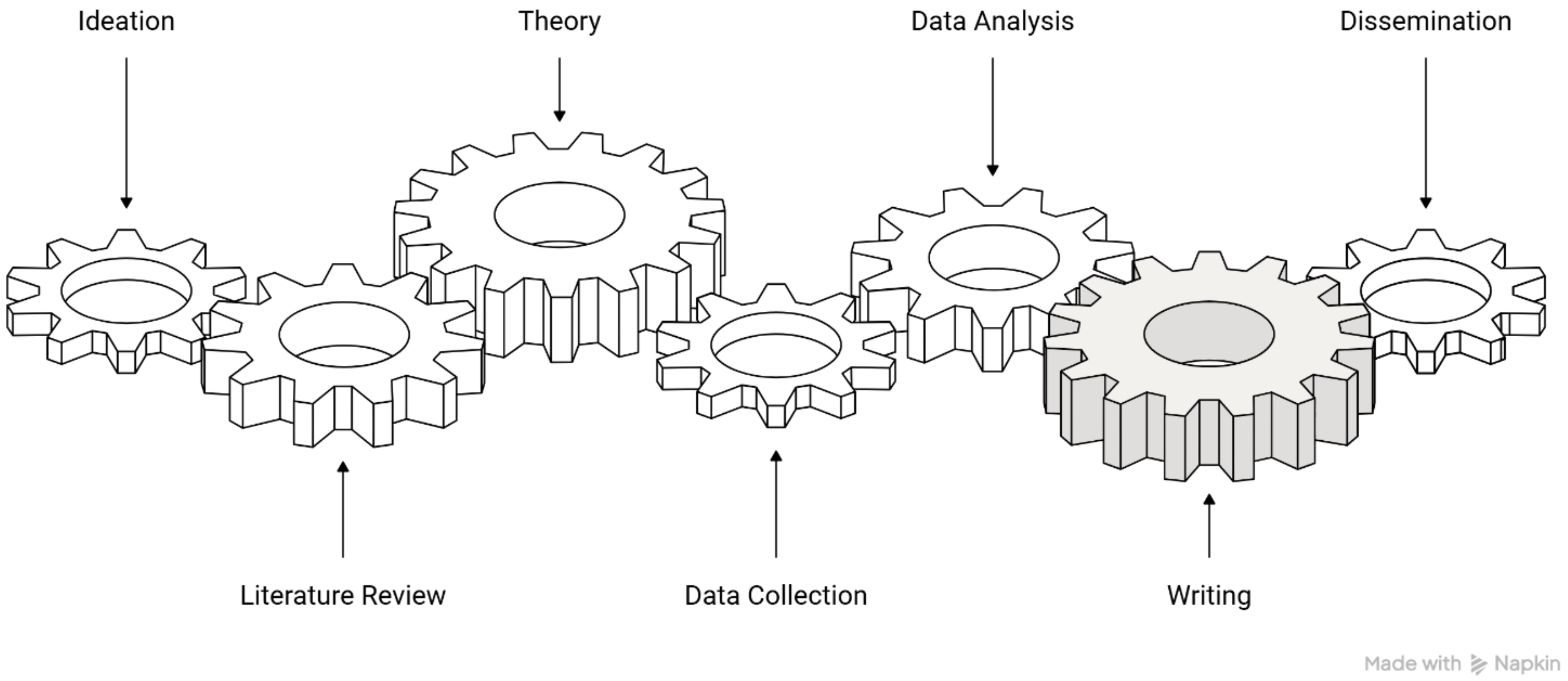
Thinking Beyond Text Analysis

- Platforms like Amazon Web Services, Google Cloud Platform, and Microsoft Azure offer access to **pre-trained ML algorithms** (via API)
- Lower entry barriers for researchers who seek to extract information from unstructured data (only basic methodological knowledge required)
  - **Image analysis**, e.g., classification, object detection
  - **Video analysis**, holistically or frame-by-frame
  - **Audio analysis**, acoustic info. or transcription



Wang, Bendle, and Pan 2024

The Academic Workflow



AI-Assisted Drafting

- <u>Remember:</u> Most academic tools are *wrappers*
- Recommended approach:
  1. Create a custom style (e.g., a Claude "Skill")
     - Define preferred style
     - Provide best practice examples (e.g., past writing)
     - Feed in target journal guidelines
     - Define negative list (expressions to avoid)
  2. Draft paragraphs in your own words
  3. Apply custom style and fine-tune
  4. Place citations manually
  5. Final check for conciseness, coherence, and readability

https://claude.com/skills

AI-Assisted Revising: Custom Approach

- Advances in **reasoning capabilities** and **context window length** enable comprehensive audits of entire manuscripts, including appendices
- **Red reading:** Diagnostic protocol that stress-tests texts across structural, rhetorical, logical, and stylistic dimensions

<u>Needed:</u> Elaborate master prompts

Prompt for consistency checks before journal (re-)submissions

Matthias Mahlendorf
Management Accounting Research (MAR) Editor-in-Chief | Academic Director of the Centre for Performance Management and Controlling

February 21, 2026

COMPREHENSIVE ACADEMIC MANUSCRIPT AUDIT PROMPT

You are acting as a meticulous academic referee, technical editor, and production manager combined. Your task is to perform an exhaustive, line-by-line consistency and accuracy audit of **all attached documents** (the main paper, the response letter to the editor/reviewers, and the online appendix, if provided). These documents form a single submission package and must be treated as an interconnected whole.

Do not summarize the paper. Do not assume correctness. Do not skip any section, table, figure, footnote, or appendix. Treat this as a formal, pre-submission quality-control review as if you were the last line of defense before the manuscript goes to the journal. Proceed systematically and explicitly document every issue you find, no matter how minor.

1. Cross-Reference and Citation Audit

1a. In-Text References to Tables

All table references (Tables 1–6 in main paper, Tables A1–F2 in Web Appendix) were checked against the actual tables. Tables are referenced in the text and exist in the document. No off-by-one table numbering errors were detected.

Status: Checked — no systematic table-reference issues detected beyond the placeholder values noted below.

1b. In-Text References to Figures

MAJOR | **Location:** Main document pp.42–43 (Figures section) Two figures are both labeled 'Figure 1 — Conceptual model.' Page 42 shows a V-Dem political polarization chart (which appears to be an additional data-description figure), while page 43 shows the actual conceptual model diagram. This creates a duplicate Figure 1 with identical captions but entirely different content.

MAJOR | **Location:** Main document pp.42–53 vs. text pp.20–25 Systematic off-by-one error throughout. The text on p.21 references 'Figure 3' for the PBG × ideology interaction plot, but the Figures section labels this as 'Figure 2' (p.49). Similarly, text references to 'Figure 4' for boundary-condition plots correspond to 'Figure 3' in the Figures section (p.50). Root cause: the V-Dem chart on p.42 is an extra figure that was inserted without renumbering the rest.

MEDIUM | **Location:** Main document pp.21 and 25 'Figure 4' is referenced twice in the text for completely different content: first on p.21 for Study 1 boundary-condition surface plots, then on p.25 for Study 2 promotional-tool effects. One of these should be Figure 5 (or the numbering cascade should be corrected once Figure 1 duplication is resolved).

1c. In-Text References to Equations

Equations 1–4 are present and referenced in the surrounding text. Due to image-format limitations, equation content could not be verified character-by-character, but spot checks confirm the text descriptions align with the equations shown. **Needs full author verification.**

1d. In-Text References to Sections and Appendices

Cross-references from the main paper to the Web Appendix (e.g., 'Web Appendix A,' 'Web Appendix Table D1') were checked. All referenced appendix sections and tables exist in the Web Appendix document. No orphan appendix items were detected.

1e. Bibliographic References

MAJOR | **Location:** Response letter p.6 vs. main doc reference list The response letter cites 'Datta, Ailawadi, and van Heerde (2017, Journal of Marketing)' but the main paper reference list has this as Datta et al. (2018). One year is incorrect. Author must verify the correct publication year and align both documents.

`review-paper` — Pre-Submission Referee Report

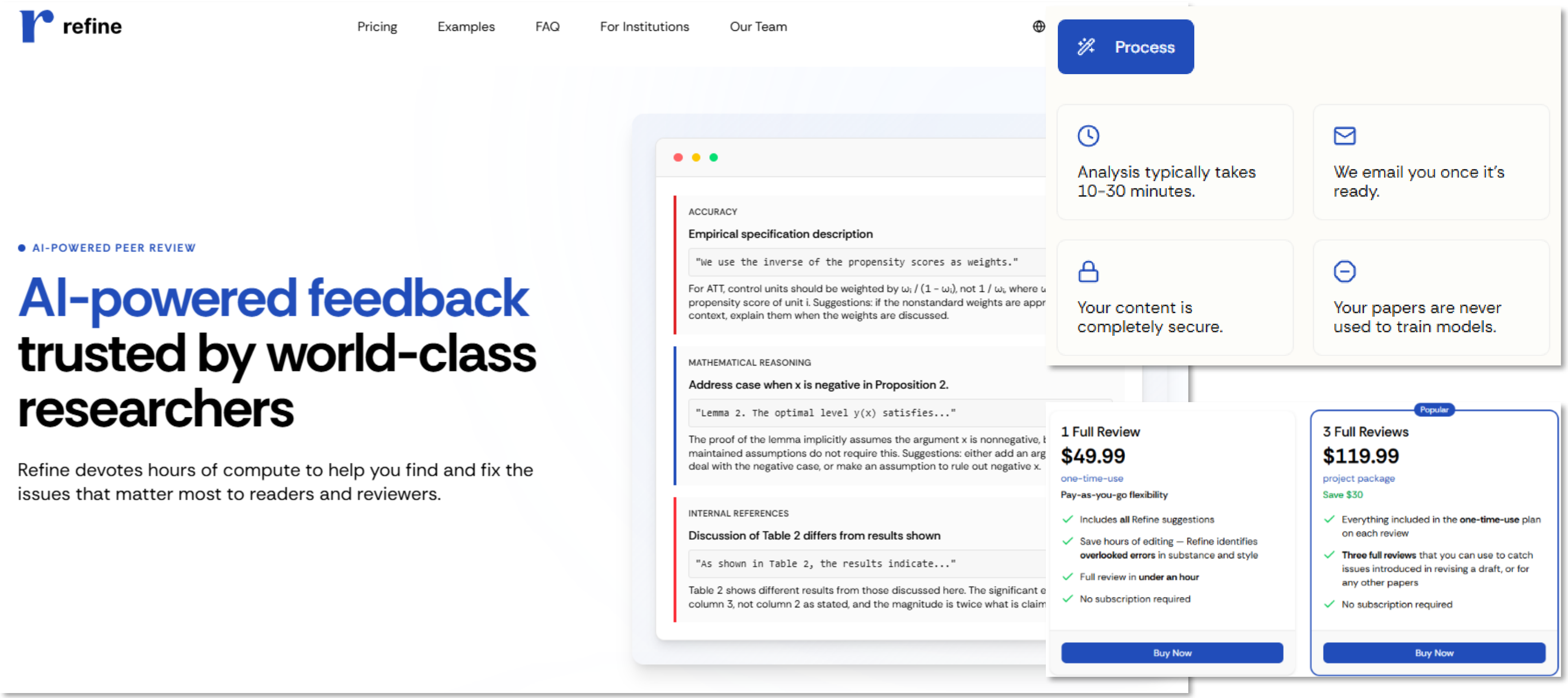
Runs a rigorous pre-submission review of an academic paper, simulating the scrutiny of a specific journal's editorial board. Six specialized review agents run in parallel and consolidate their findings into a single structured report.

What it reviews:

Agent	Focus
1	Spelling, grammar, and academic style
2	Internal consistency and cross-reference verification
3	Unsupported claims and identification integrity
4	Mathematics, equations, and notation
5	Tables, figures, and their documentation
6	Contribution evaluation (adversarial journal-specific referee)

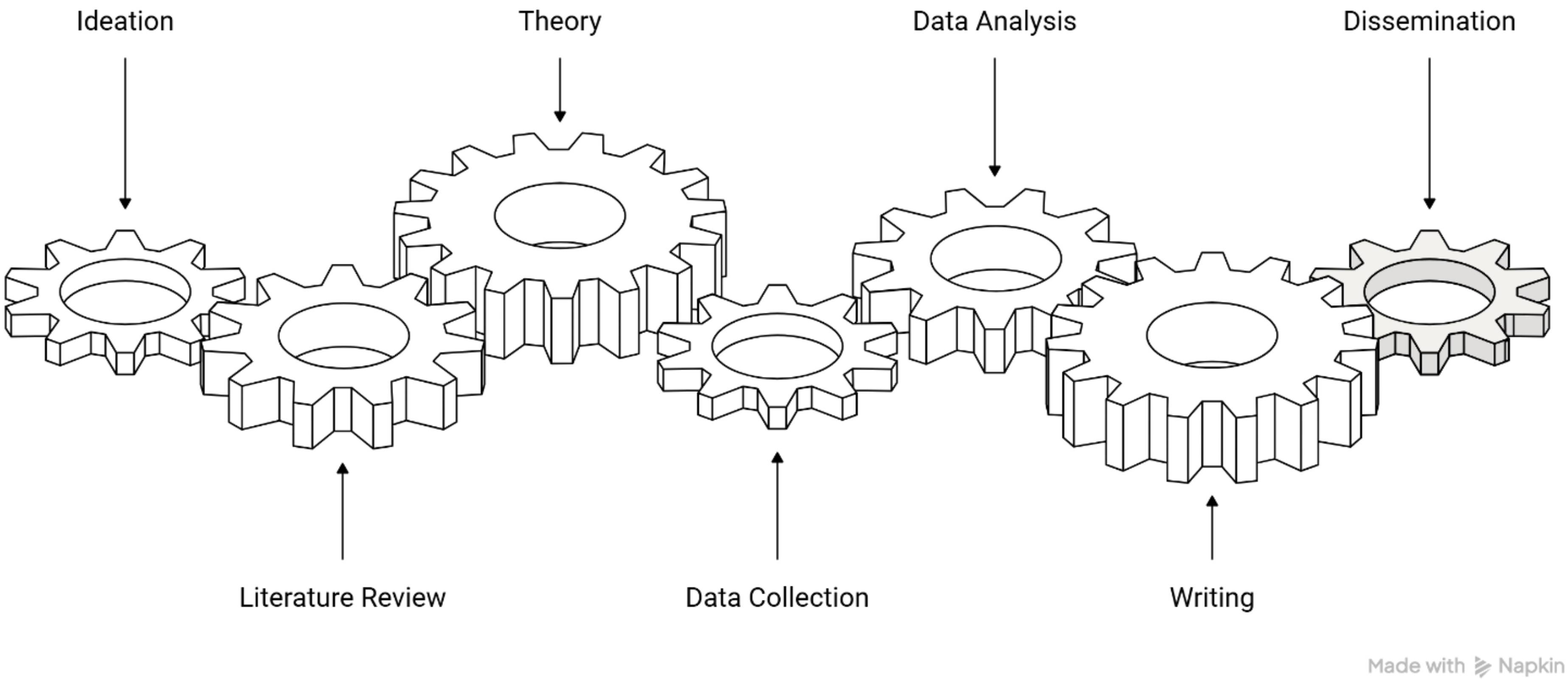
Floridi, Morley, and Novelli 2025 | https://tinyurl.com/revision-audit | https://github.com/claesbackman/AI-research-feedback

AI-Assisted Revising: Wrapper Approach



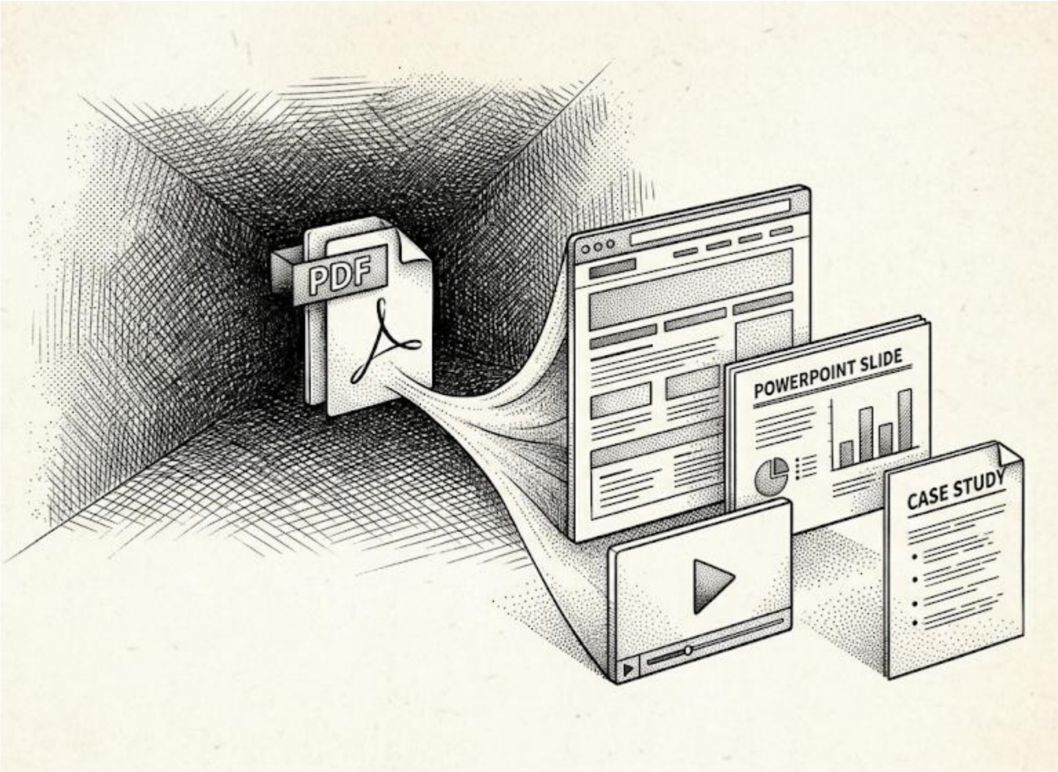
https://www.refine.ink/

The Academic Workflow



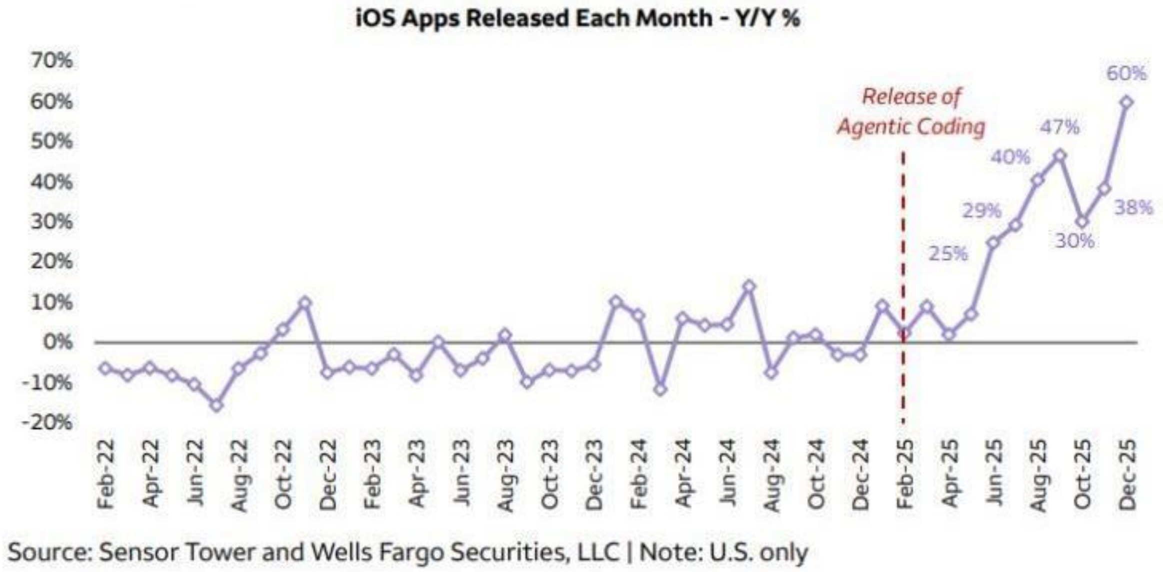
How to Get Your Message Out There

- Don't let your academic output be just a single line in your CV pointing to a PDF file behind a paywall
- Creation of **spin-off content** (e.g., web applications, explainer videos, teaching slides, teaching cases) has never been easier



Everyone’s a Programmer Now

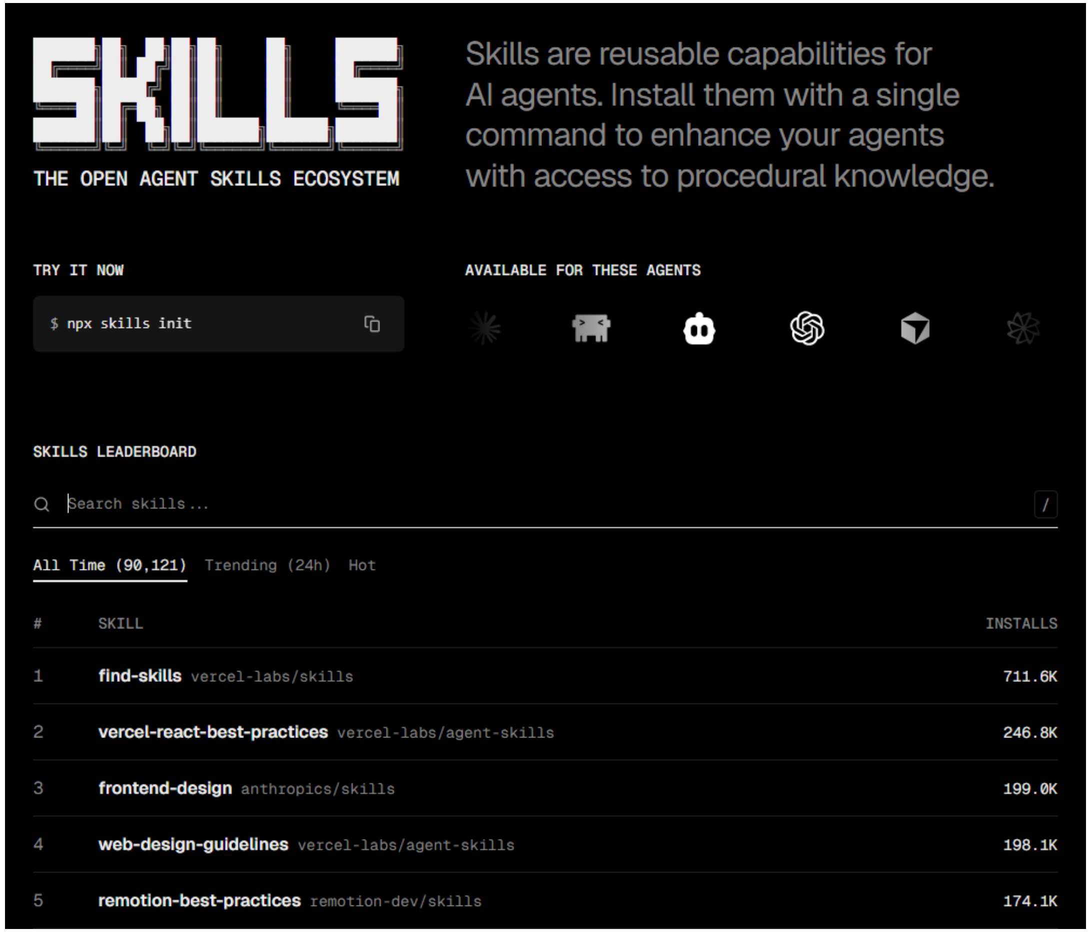
- **Agentic coding tools** (e.g., Claude Code) revolutionize programming
- Basic programming knowledge can help achieve better outcomes



How to get started with Claude Code: https://ruben.substack.com/p/claude-code

Generate Spin-Off Content

- Virtually any digital document (e.g., .docx, .pptx, .pdf, .xlsx) is ultimately built from structured formats
- Hence, agentic coding tools can generate them all
- **Custom “skills”** improve the outcome drastically
- Skills (simple .md files) are transferable across platforms



Agent Skills Directory: https://skills.sh/

Wrapping It Up

- Moving from *prompting* to *collaborating* unlocks significant **efficiency gains**
- **Shift towards AI agents** (*delegating*) is in full swing (e.g., Economics, Finance)
- Trend reinforces the need for
  - a robust **method training**, and
  - a good overview of available **tools and resources**

  to be able to effectively direct and supervise.
- **Use of APIs** is key to benefit from a broad range of capabilities at scale
- **Skills** are extremely useful for fine-tuning various tasks along your workflow

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