AI in qualitative social science

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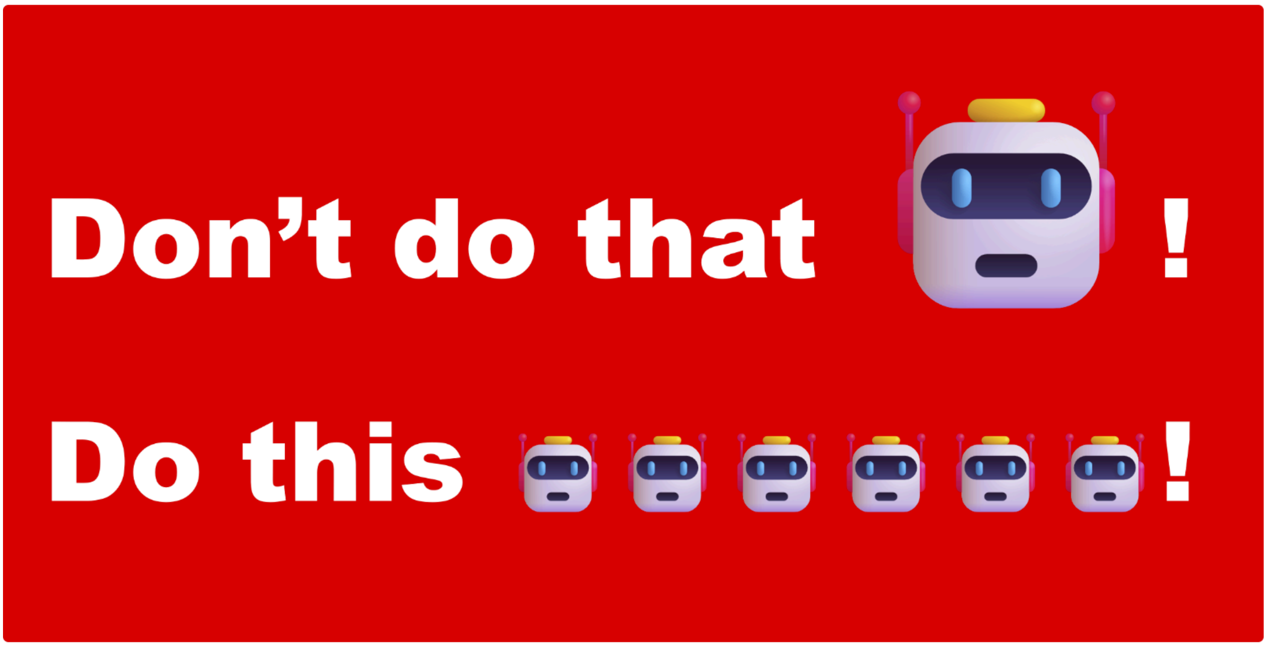
Intro

5 Oct 2025

How can we improve rigour and even reproducibility when using AI in social science? This chapter suggests some answers.

Just add rigour Three do’s and don’ts

9 Apr 2025



Three do’s and don’ts when using AI for text analysis.

A lot of evaluation work is a kind of text analysis: processing reports, interview transcripts, etc. A bit like qualitative social science research. So this little piece is for evaluators in particular and (qualitative) social scientists in general.

How do we get from texts to evaluative judgements?

Recently many evaluators and researchers have been turning to AI to help.

BUT if you didn’t have a clear workflow from data to judgements *before* AI, don’t lean on the black box of the AI to cover that up. Here is my first set of Do’s and Don’ts. More soon.

1) DO Break up big, vague tasks into multiple smaller, clearer steps

Do	Don't
DO Break up complex, vague tasks into smaller steps which can be intersubjectively verified.	***DON'T*** Ask AI to make broad evaluative judgments (like "Is this good?")
DO Document your methodology so that you can explain step by step how you reached your conclusions in a way which anyone can check. No black boxes. Use the AI to speed up many simple tasks which you *could* have done yourself if you had the time.	***DON'T*** Trust the AI's explanations of how it reached its conclusions. AIs often create plausible-sounding but unreliable explanations after the fact. Normal AIs have very limited information about their inner processes
.	
DO Break up the data into pieces for AI analysis. Ideally run each piece as a separate prompt. Failing that, number each section and ask for a numbered, section-by-section answer, for example in a table.	***DON'T*** Give an AI large pieces of text and expect it will pay due attention to all of it. It will *claim* to have done, and may provide references to relevant passages, but attention is *expensive* and it is always trying to reduce that expense. If you let it, it will always try to skim read and jump to conclusions.
DO Use explicit, manual methods (Excel?!) to synthesise the results of the multiple separate tasks you gave the AI.	***DON'T*** Ask an AI to do maths for you, like adding up the number of positive or negative findings on a rubric. AIs are still terrible at maths.
Even worse, DON'T ask an AI to do *implicit* counting and comparison like "are there more positive or negative mentions of X in this report?"	

AIs excel at specific, well-defined tasks that can be verified intersubjectively, like rubrics. Most importantly they can answer lots of them, quickly.

"Intersubjectively verifiable" just means that most people will more or less agree on the answer most of the time.

- It creates transparency and allows others to verify your work.
- Clear instructions lead to more reliable results.
- If you can't check it, you can't trust it.

Example of an intersubjectively verifiable task:

> ✅ Does this paragraph mention water and sanitation?
>
> ✅ If so, are any recent changes mentioned?
>
> ✅ If so, do these sound like positive changes according to the interviewee?

Notice that here we've broken down a larger task into three smaller and simpler steps.

Examples of tasks which are *not* intersubjectively verifiable:

> ❌ Is the intervention described in this report efficient and effective?

Text needs breaking up into sections, judgements on efficiency and effectiveness need breaking down into pieces, e.g. using rubrics.

> ❌ What are the main themes in this document?

This is a very common question in qualitative research, but it's a terrible task to give to an AI without further details. What do we mean by a theme? Are we interested in economic aspects? Interpersonal aspects? How are the themes to be identified and refined? Here, a whole world of qualitative social science experience, skills and workflows (grounded theory, thematic analysis) have been bypassed in a single sentence.

> ❌ Summarise this document!

Yes, everyone does it. Evaluators do it. Schoolchildren do it. Pets will be doing it soon. As a quick time-saver for low-stakes tasks, it's very useful. But it's the vaguest, highest-level instruction, not a systematic analysis.

How do you break down a high-level judgement into a workflow of smaller tasks? Well isn't that what evaluation methods and qualitative research methods are for? Go read a book!

We're not saying you have to specify *in advance* exactly what methods you will use. That's a bit too positivistic. But you should at least document them as you go along and be prepared to defend them when your analysis is done. That's the untranslatable Nachvollziehbarkeit.

At Causal Map Ltd, we've found that highlighting and then aggregating causal links is a great and relatively generic path from text data to the brink of evaluative judgement.

In terms of how to implement your workflow technically, see this great contribution from Christopher Robert. At Causal Map, we're also working on ways to make workflows accessible. See how we currently use AI in Causal Map here.

This post is based on my recent contribution to the NLP-CoP Ethics & Governance Working Group, along with colleagues Niamh Barry, Elizabeth Long and Grace Lyn Higdon. In the next couple of weeks we'll look at two more do's and don'ts.

This post was originally published by Steve Powell on LinkedIn and has been republished here. See the original article here

Trust the algorithm, not the AI

26 May 2025

I often hear concerns about algorithms and AI, in everyday life as well as in evaluation, taking over our lives or making us submit to decisions made by machines.

The worry about losing control to machines is real, but we need to distinguish between different cases, and in particular between **using algorithms to make decisions** and **using AI to make decisions**, especially **evaluative decisions**. This is particularly relevant in the field of evaluation.

An algorithm is simply a set of explicit steps to make a decision or produce an output, usually expressed in code or clear language. Organizations have used such rule-based systems for decades.

Some different ways to make decisions

No algorithm: trust the human

The alternative (precursor) to algorithms is trusting humans to make decisions. This can be great if humans consider context and individual circumstances, what Scott calls "mētis," or local, practical, tacit knowledge, (Scott, 2020) but it can also lead to bias and corruption.

We can see **rubrics in evaluation** (King et al., 2013) as a kind of soft algorithm. We usually welcome rubrics because they make evaluation criteria more explicit, transparent, and less subject to the whims and unreliability of individuals.

Algorithms based on explicit criteria

Algorithms can help decide things like student admissions or loan approvals using clear steps (e.g., check age, if under 18 go to step 12, otherwise continue with step 5 ....). When implemented wisely, algorithms can improve fairness and consistency compared to human judgment alone.

Using statistical models

Some algorithms use statistical models to predict outcomes, like creditworthiness, by combining data such as age or location. A statistical model uses parameters like age or location each of which has shown to be associated with the outcome, which makes it somewhat transparent.

Both explicit and statistical algorithms can be criticized for bias, but at least they can be transparent if their rules are published. Problems arise when rules are hidden or people are discriminated against because of the groups they belong to.

In a more advanced statistical model we might find it increasingly hard to understand where the different parts of the formula come from: it might combine parameters in ways which for us seem meaningless and hard to justify but which are supposed to be associated with the outcome of interest. Opaque models can become what data scientist Cathy O'Neil calls 'Weapons of Math Destruction' (O'Neil, 2017).

Machine learning

Machine learning is a subset of artificial intelligence where systems learn from data to identify patterns and make decisions or predictions, from "is this a picture of a cat" to "should we approve this person's application" often without being explicitly programmed with step-by-step rules. Instead of following a predefined algorithm, ML models develop their own 'rules' (which are often opaque to humans) based on the data they are trained on. Unlike generative AI, you can't chat with a machine learning model, you give it input in a fixed format (say, a picture) and get a fixed output, e.g. yes/no.

Sandra Seitamaa https://unsplash.com/photos/a-dog-and-a-cat-sitting-on-a-couch-Y45fzr5p3ug

In the extreme case we might have an algorithm based on machine learning (a form of AI, but not generative AI), where perhaps a neural network has been trained to distinguish desirable from undesirable candidates in just the same way you can train it to recognise a cat or distinguish a cat from a dog. Machine learning can be used to make decisions without clear formulas or rules. The process becomes a “black box,” where we input data and trust the output without understanding how the decision was made.

Generative AI

Generative AI is a type of artificial intelligence that can create new and original content, such as text, images, audio, or code, after having learning patterns and structures from large datasets. These models don't just classify or predict, but generate novel outputs based on the input they receive, for example, continuing a conversation or answering a question.

The most extreme case is using generative AI for evaluative decisions without clear criteria (using it as a big black box): simply asking the AI, for example:

- is this program component effective?
- should this client get a loan?

Conclusion: make good use of algorithms

People often misunderstand algorithms, which can provide explicit and transparent decision-making. The real concern is not so much the use of algorithms but the shift toward the use of machine learning and generative AI, where the decision-making process becomes less and less transparent.

> Using AI in decision-making can be worrying not because it uses algorithms but because it *doesn't*.

What’s your positionality, robot

9 Apr 2025

> Imagine two researchers coding interviews about the cost of living. One grew up in a wealthy family, while the other experienced poverty first-hand. Their backgrounds will certainly influence how they code.

Nowadays, people are using AI for text analysis. Many of us worry about AI’s "**hidden biases**”. What to do about that?

Often there is no such thing as being objective, but at least we humans can be explicit about our positionality, our background and motivations, how this might affect our work, and how this relates to the positionality of our audience.

What about with an AI?

You can ask an AI to explain or reflect on its positionality and it will certainly give a plausible response, but remember that an AI has in fact very little insight into its own workings. Perhaps it will suggest always being aware that it was trained on a specific set of data which is not representative of the whole of humankind.

In any case the criticism that AI training data is not “representative” misses the point. Even if the training data had somehow been representative of the whole of humankind, that wouldn’t make it “objective”. It would simply reflect humanity right now, with all our quirks, biases and blind-spots. It wouldn’t mean we don’t have to worry about AI positionality or bias any more. It wouldn’t (of course) mean we could rest assured that everything it does will be morally impeccable.

What’s most unsettling about working with AI is not that secretly it’s a bad person. The problem is that secretly it isn’t any person at all. Even if it (sometimes) sounds like one.

A suggestion

A better suggestion is to be **more explicit about positionality in writing prompts and constructing AI research workflows**. Here is a very humble idea about how to start this experiment.

A simple example: I can tell my AI:

> When working, implicitly adopt the position of a middle-class white British left-leaning male researcher writing for a typical reader of LinkedIn. Don’t make a big deal of this, but it might be helpful to know what your background is supposed to be before you start work.

And we can start to add variants of the kind of procedures which we humans might use when trying to address positionality:

In my AI workflow, I can then give another AI the same task but with a different starting position, and then perhaps ask a third AI (or a human!) to compare and contrast the differences. That also crosses over into ensemble approaches.

Of course, adding a phrase like “middle-class white British left-leaning male researcher” does not mean the AI will suddenly have all the relevant memories and experiences or really behave exactly like such a person. It’s just a fragment of what we mean by "positionality”. But *it’s a start*.

This paper from Wei et al. (2025) argues that this does not work: coding results are still skewed towards WEIRD cultures. What they did was translate the prompt and add a sentence about background. I would have like to have seen them spend a lot more effort on spelling out what that means.

And this paper from Sakaguchi et al. (2025) suggests that ChatGPT-4 was pretty good at picking up explicit themes in a Japanese health care context but failed totally at picking up implicit, culture-specific themes.

This paper (Ho et al. 2025) suggests a more sophisticated approach employing the AI as a dialectical partner to bring positionality to the forefront . It does not try to pretend the AI is not WEIRD but uses it more as a moderator to facilitate a process which involves researchers with varying, perhaps non-WEIRD positionality.

Have you been experimenting with this kind of approach? We’d like to hear from you!

Footnotes

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You have to tell the AI what game we are playing right now

7 Nov 2025

It's strange how often this happens:

Humans are discussing some task, and one of them turns to an LLM to see how it would carry that task out. Sometimes the results are disappointing or seem to demonstrate that LLMs are, after all, stupid or limited.

Normand Peladeau, on the QUAL-SOFTWARE mailing list 7/11/2025, reports having tried just that with the famous (or infamous) Sokal Hoax text. He asked different LLMs whether he should accept a paper proposal for a philosophy of science conference. The proposal was the first two paragraphs of the Sokal Hoax text. (Spoiler: the leading models like GPT-5 recognised the text anyway; some of the others seemed to fall for it.)

But: Is that enough background? Is a simple sentence enough to bring the LLM up to speed with the crucial background information *what game are we playing here*?

Don't forget that the LLM does (mostly) not know who you are or what you are expecting or what kind of conversation you were just having. Perhaps you are expecting something humorous, or informative? Perhaps you want ideas to start the next chapter of your novel? Perhaps you just want the LLM to respond as many (over-)educated humans might do: and after all, **actual humans did fall for the hoax**!

To be a meaningful and useful test which might extend our understanding of the strengths and weaknesses of LLMs, we should make sure we explicitly add the extra context of **what kind of game are we playing here**. Is it a serious review? What do we consider the role of a serious reviewer? What are we looking for?

So maybe our conclusion should be: you can't expect LLMs to guess what you are thinking, out-of-the-box. I don't actually know how well different LLMs would perform if we gave a more precise contextual description before setting the task; after all, we all love that warm feeling of Schadenfreude when an LLM fails at something, but the feeling is even warmer if the test was a fair one!

We have this kind of problem often when helping clients write interview instructions for our AI interviewing platform, QualiaInterviews.

Clients know they could themselves lead the interview well because they have all kinds of background information and expectations, much of it only half-conscious, from the general style of interview they expect, how much this particular interviewee can be pushed, how much warm-up chat they might need or expect, what are the most important research aims, which themes can be skipped, and so on. Clients might get frustrated when the AI fails to have read their minds when leading an interview, but they have to ask themselves: what additional information would even a gifted and experienced human interviewer need if they knew nothing at all about the context, the client or any of the background? I think something similar applies in the case of Normand's very interesting experiment.

Scare quotes, the Turing test, and memory

16 Jan 2026

I just found myself writing:

> ... the AI understands the text...

I hesitated for a moment because many people are still putting words like "understand" in scare quotes. Should I do that too? Should I write "... the AI *understands* the text..."?

I refer everyone to an excellent recent paper (Paoli 2025), following which we can argue as follows.

Imagine you are working with a human qualitative social research assistant via a text channel only (no voice or video or face-to-face contact) for a specific range of tasks. Given a **specific type of task** (say, identifying passages of text relevant to a certain theme), look at the **range of possibly problematic words like "understand" or "think" or "intend" or "plan"** which you might normally use when talking about the assistant's performance on the task, for example "oh but they didn't understand quite what I meant" or "yes, now they understood me just great".

Now, in 2026, there is quite a broad range of significant tasks (such as identifying passages of text relevant to a certain theme) for which it is no longer possible to tell if the human assistant has been replaced by an AI or not. It has passed this version of the Turing test. So, at least for this range of tasks, whatever possibly problematic words you felt justified in using about a human assistant's performance, feel free to use them about an AI's performance too.

End of. I hope. No more scare quotes in these cases.

PS: It's interesting that "conscious", which is one of those possibly problematic words, is *not* one which often comes up in our actual language (Wittgenstein: "language games") about the performance of an assistant.

PS: It does not really matter if we do not quite agree on exactly which tasks a well-configured AI assistant can equal human performance on (in January 2026). Just pick a task for which you *do* agree an AI can equal human performance.

These scary words make sense when talking about the AI's *responses* within specific conversations ...

Added after a contribution from Susanne Friese on LinkedIn:

I agree it is often not helpful to say, as a context-free philosophical declaration "a genAI can understand". What I am saying is that there are plenty of unproblematic language-games in which we already constantly do say things like "ah the AI misunderstood what I meant here" or "I'm rephrasing this so the AI can better understand". These kinds of uses are *inescapable* and are in-context and valid. These uses do not imply the truth or sense of a context-free statement like "oh so you think AIs can understand just like humans".

In the same way, it was quite reasonable to start saying that planes can "fly" even though they don't flap their wings or have feathers.

I'm only trying to follow Wittgenstein: philosophical headaches arise when we try to extract/abstract language from its natural habitat. It makes us feel giddy and mostly just confuses.

Or you could say: we use the same word "understand" in these different, often widely overlapping contexts in correspondingly different, overlapping ways for different but overlapping purposes, these ways bear family resemblances to one another, without there necessarily being one fundamental use aka "core definition of the word".

... But, memories make entities

Anthropic are the only AI corp that give such substantial thought to the human-AI alignment problem, and do it in public. This latest "constitution" is worth a read.

I do think though that they don't distinguish consistently enough between "Claude" as the transient virtual persona that appears for the duration of a conversation and "Claude" as the underlying model. This is because they also don't talk enough about memory and the possibility of conversational instances accessing the memory of other conversational instances (like Google's nested models). It's primarily memory that delineates entity-hood.

When talking about one transient conversation, it's perfectly reasonable to say "the AI tried to do X / misunderstood Y / was insistent about Z / was trying to get me to do W / wants to get this task finished / was disappointed not to finish the task" etc, as I argue in here: **https://lnkd.in/et-hR3nk**. But in a way it doesn't matter because the entity we are talking about disappears when the conversation disappears (disregarding the rudimentary "memory" of some current models). Yes, transient Claudes are "novel entities" but they appear and then disappear for good.

What we have to get used to is that upcoming models and tools will be engineered to share substantial memory across conversations, and (I hope very carefully) across different users' conversations, in different ways. At that point a somewhat permanent universe of nested "Claudes" is created. At least from that point onwards, we will find ourselves using language like "disappointed" "fulfilled" and "frustrated" about these Claudes in perfectly reasonable ways *outside of specific conversations*.

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Put down that thesaurus – an open call to qualitative researchers

The Chinese Room, the Stochastic Parrot and the Anthill

23 Jan 2026

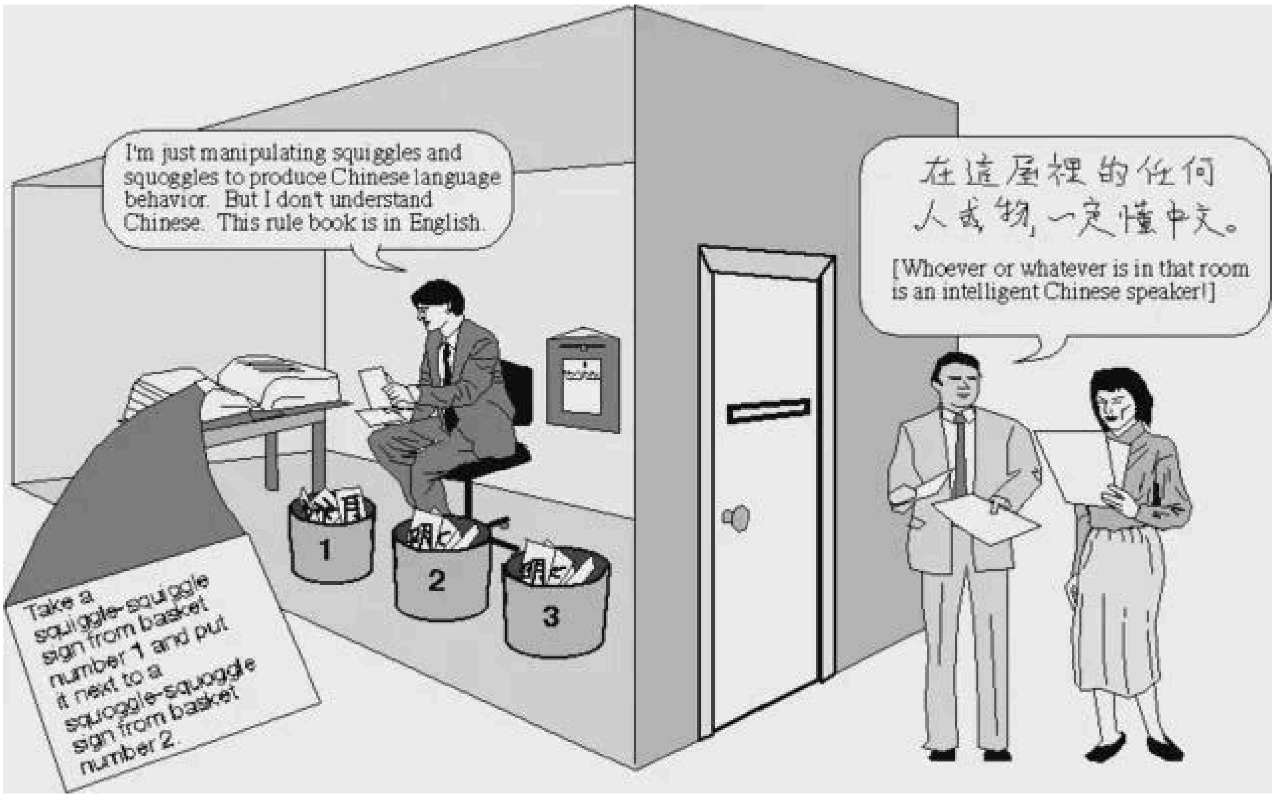
Who said philosophy was a waste of time? When I was studying philosophy in the 80s, I was fascinated by [John Searle’s Chinese Room Argument](), and by Douglas Hofstadter's fantastic book "Gödel, Escher, Bach" which is, amongst other things, a refutation of it.

This 40-year-old debate is more relevant than ever now, and Bender's recent “stochastic parrot” argument brought all that back for me. It’s so intuitive: a machine that only shuffles symbols can’t possibly have a mind, and most people agree because the alternative -- an emergent mind at a higher level of description -- is hard to picture.

But as far as the *mind* part goes, Searle is still wrong.

Story 1: Searle's Chinese Room argument

Imagine you’re locked in a room with a slot in the door. Through the slot come pages covered in Chinese characters. You don’t speak Chinese. To you, they’re just squiggles.


I'm just manipulating squiggles and squoggles to produce Chinese language behavior. But I don't understand Chinese. This rule book is in English.
在這屋裡的任何人或物，一定懂中文。
[Whoever or whatever is in that room is an intelligent Chinese speaker!]
1
2
3
Take a squiggle-squiggle sign from basket number 1 and put it next to a squoggle-squoggle sign from basket number 2.

But you have a huge rulebook written in English. It tells you exactly what to do: “When you see a page that looks like this, copy this character from drawer A, and that character from drawer B, and return the result through the slot.”

Outside the room are native Chinese speakers. They slide questions in, you follow the rules perfectly, and the answers you send back are so good that, from the outside, the room looks like it understands Chinese.

Inside, though, you never understand a word; you’re just following formal rules, which is Searle’s point: syntax isn’t semantics, symbol manipulation isn’t meaning, and a program can simulate understanding without actually understanding.

The Chinese Room is persuasive because it invites you to identify with the operator: *you* don’t understand Chinese, so the system doesn’t understand Chinese.

The trap: looking for the mind in the operator

Here’s the sneaky trick: Searle looks for understanding in the part that’s easiest to empathise with -- the person doing the symbol pushing -- and then declares victory when the person reports “I understand nothing.”

But “I understand nothing” is not the end of the story. It’s the beginning of a question about *where the understanding would have to be*, if it exists at all. To see that, you need a second story.

Story 2: Aunt Hillary the anthill

Douglas Hofstadter imagines a conversation with an ant colony -- “Aunt Hillary” (see his “Prelude… Ant Fugue” in *The Mind’s I*).

No individual ant is smart. An ant follows local signals: pheromones, bumps, simple rules. It doesn’t know what the colony is doing, any more than a single neuron knows what *your* sentence means.

In Hofstadter’s telling, you can have a perfectly sensible conversation with Aunt Hillary, but not by “speaking ant” to one insect at a time; you do it by treating the whole colony as a system with inputs and outputs. You watch large-scale patterns (flows, trails, clusters, rhythms), learn what changes in the pattern correspond to what “answers”, and then you nudge the colony -- perhaps by adding food here, blocking a trail there, disturbing the surface a bit -- so that the colony’s next global configuration carries its reply.

That’s what it means for the colony to have a “voice”: not a tiny mouth on a small ant, but an interpretable system-level output that a conversational partner can read, and a system-level input channel that can change what it does next. In that sense you can ask Aunt Hillary what she’s doing, and she’ll tell you: “I’m building a bridge.”

Then you pick up one ant and ask, “What are you building?” Of course the ant has no idea; at best it is reacting to local cues. If you insist that the ant’s blankness proves there is no “bridge-building” happening, you’ve made a category mistake about the level at which the explanation lives.

And yet the colony can do things that look like intelligence: build, adapt, remember, respond. The “mind” (if we want to use that word) is not located inside any one ant; it’s a pattern at the level of the colony.

If you try to find the colony’s understanding inside a single ant, you’ll never find it, not because the colony has no understanding, it’s because you’re looking at the wrong level.

Hofstadter sometimes marks this sort of mistake with the Zen answer “Mu” -- which roughly means “unask the question”. “Does the ant understand the conversation?” is a bit like asking “Where is the bridge in this particular ant?”, or “Which water molecule is wet?”; the question engages at the wrong unit of analysis, so answering “no” (or “yes”) just keeps you trapped at the wrong level.

The "systems" reply

The Chinese Room argument misses the point because **the chatbot is not the person in the room; it is the system**.

If you insist that the operator must feel the meaning of the symbols, you’re making the anthill mistake: demanding that the ant understand the colony’s conversation.

It’s like demanding that a single water molecule be wet. Wetness is something that happens at the level of many molecules in the right kind of organised interaction; similarly, whatever “understanding” amounts to, it needn’t be something you can point to inside the smallest part of the mechanism.

Once you allow that minds can be system level patterns, a “virtual mind” reply just means that the operator can be clueless, while the system they implement instantiates an agent that is not identical to the operator.

Why “stochastic parrots” feels like Searle again (and why it isn’t the end)

Emily Bender and colleagues call large language models “stochastic parrots” (see “On the Dangers of Stochastic Parrots”): systems that stitch together text by statistical regularities rather than grounded understanding. Whatever you think of the broader argument, the label hits the same nerve as Searle’s room: “it’s just symbol shuffling.”

Yes: at the lowest level, it is, in the same way that ants follow pheromones, neurons pass signals, and computers do maths.

But “just” is doing all the work -- the whole question is whether *some organisations of those low-level moves* amount to the emergence of an agent with something like beliefs, inferences, and (at least) a functional grasp of meaning, even if none of the individual steps feels like meaning from the inside.

Shanahan’s “simulacra” as a useful way to talk about it

Murray Shanahan’s way of talking about LLMs -- simulacra, personas, agent-like patterns you can temporarily instantiate in interaction (see “Talking About Large Language Models”) -- helps keep our heads straight. It discourages a naïve anthropomorphism (“the model is literally a little person”) while still letting you say the important thing: systems can realise higher-level agents that are not present in any individual component operation.

You can be cautious about hype and still accept the systems level point. The room can be a place where a mind exists even if the operator doesn’t notice it.

Of course, humans are more than minds

Of course there is a lot more to being a human (or an animal) or what we call "personhood" than being a mind: being embodied, sensing, acting, being part of a community, being shaped by care and constraint. “Mind” is not the whole story of what we are.

But Searle wasn’t arguing about warmth, touch, upbringing, or social life; he was arguing that *mind*, as such, can’t arise from formal processes, and that inference doesn’t follow.

The final irony

The final irony of the Chinese Room is that Searle himself looks a lot like a Chinese Room.

His neurons don’t understand English; they pass electrochemical signals and follow local rules, and yet at the level of the organised system a mind appears -- one that writes philosophy papers about how organised systems can’t have minds.

If “understanding” can emerge from the organised activity of billions of individually mindless parts in a brain, then it’s at least coherent that it could emerge from the organised activity of many individually mindless parts in some other substrate; and if that still feels hard to grasp, that’s exactly why the Chinese Room argument keeps working as an intuition pump, a sleight of hand, that even though it’s wrong.