Will Artificial Intelligence Put Mathematicians Out of Work?

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SKIP THE NOTES

25 July 2026

[1] Correct information at BU webpage | Almost correct but not quite ... | Almost correct but not quite ... | معلومات تقريبية وغير مكتملة ...

NOTES for slide 1:

- Many slides are not numbered and without a grey banner (like this one). These contain my notes, which I intend to present verbally during the lecture. I intend the actual presentation with the overhead projector to be limited to the numbered slides with a grey banner.
- I have inserted hyperlinks to places on the Web to back up many of my claims. These are identified by a green frame like *this.*
- I composed my slides for an audience which I anticipated to primarily include ***mathematicians***, ***computer scientists***, and other mathematical scientists, such as ***theoretical economists***, ***theoretical physicists***, some ***engineers***, and others whose work depends on rigorous mathematics.
- I refer to all these people by calling them "*mathematicians*" , *i.e.*, practitioners of mathematics, even though they are not known as *mathematicians* professionally.

Abstract / Summary

- ***Mathematics*** is a scientific discipline that has existed for more than two millennia, always sustained by a thriving community of people — ***the mathematicians*** — constantly engaged in problem formulation, exposition, professional meetings, teaching, refereeing, informal give-and-take, and a lot more.
- By contrast, ***Artificial Intelligence*** (AI) emerged as a distinct and separate scientific discipline about seventy years ago, which moreover cannot exist and develop further without its mathematical foundation. While AI owes its very existence to mathematics, and mathematics has been and will continue as the foundational backbone of many other disciplines — ***the mathematical sciences*** — there are yet influential commentators and decision-makers of the hi-tech industry that are all too prone to predict that mathematics will become obsolete and lose its privileged position because of AI within a few years.

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- This lecture examines this prediction critically by considering three AI systems — ***Large Language Models*** (LLMs), ***Automated Theorem Provers*** (ATPs), and ***Interactive Proof Assistants*** (IPAs) — and asking what parts of mathematics each requires, what math problems each has actually solved or has assisted in solving, and what kind of math problems each is likely to solve in the future.[2]
- The evidence reveals a different picture: LLMs can be very good in assisting to solve math problems (without absolute guarantee that they will succeed) but cannot discover new mathematics without guidance and even prodding by human mathematicians. By contrast, ATPs and IPAs excel at certifying, at verification, and at formalization, and yet not at discovery.[3]

[2] There are many other AI systems besides LLMs, ATPs, and IPAs, the latter being the AI systems that probably depend the most on — or interact the most with — **mathematical logic**.

[3] **Discovery** for a mathematician — such as developing an *intuition* for a problem, or an *aesthetic* view of it, or an *alternative perspective* from another area of math on the same problem, or a *new mathematical ability* (some people are better at manipulating numbers, others at drawing geometric figures) — is more than *verifying* a conjecture or *certifying* a proof.

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- None of the three aforementioned systems stands out for promoting an aesthetic dimension of mathematical concepts in ways that mathematicians had not already experienced in pre-AI times — and, significantly, often at a slower pace more appropriate for human reflection. Mathematics is not just problem-solving and delivering theorems to publishers; it is far more than that: it is about insights and intellectual understanding, and (yes!) pleasure and beauty, and many other fulfilling things for its community of human practitioners.
- Rather than displacing mathematicians, these AI systems reveal mathematics to be more essential than ever — as the very foundation on which AI systems are built, and as the discipline most capable of ensuring the rigorous use of AI systems and developing (conceptual) guardrails against their malfunctioning.
- This lecture concludes that mathematicians and their practice are not really at risk — if they face a risk at all, it is antagonizing those who control the purse and their salaries — instead, their roles are evolving, expanding, and indispensable.

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Outline

Part I

AI and Mathematics: A Mathematician's Perspective

Parts of Mathematics on Which AI Depends

LLMs, ATPs, and IPAs are mathematical constructions through and through:

- ***LLMs:*** Their foundations include *probability, statistics, information theory, optimization, linear algebra, calculus,* and *numerical analysis*.

  Their core mechanisms include neural networks, embeddings, and gradient-based optimization, with attention mechanisms enabling LLMs to process sequences effectively.

- ***ATPs:*** Their foundations include *mathematical logic* and *proof theory*.

  Their core mechanisms include unification, term rewriting, satisfiability solving, decision procedures, proof search, and model checking. *Machine learning* may guide search but is not required for correctness.

- ***IPAs:*** Their foundations include *mathematical logic, type theory, lambda calculus,* and *proof theory*.

  Their core mechanisms include rewriting, normalization, elaboration, and trusted proof checking. LLMs may propose proofs, but the kernel certifies them.

  References for further reading:

  Attention Is All You Need

  Deep Learning

  A Survey on Deep Learning for Theorem Proving

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NOTES for slide 12:

- One point to insist on is that the mathematical foundations of LLMs, ATPs, and IPAs are themselves in constant evolution. New results in these foundational areas enable better designs and implementations of all three systems. Ignoring such developments would forfeit significant opportunities for improvement.

- For example, *machine learning* depends on mathematical structures at every level: the representation of data as vectors; the optimization of parameters; the probabilistic interpretation of prediction; and the numerical analysis of large-scale computation. The Transformer architecture in the article "*Attention Is All You Need*" by Vaswani et al. is another useful example: *attention* is presented as a concrete algebraic and probabilistic mechanism for relating vectors in a sequence, not as a magical replacement for mathematics. Deep learning, as surveyed by LeCun, Bengio and Hinton in their article "*Deep Learning*", likewise rests on differentiable computation, gradient methods, statistics, and high-dimensional representation. The same is true on the symbolic side: ATPs and IPAs are direct descendants of *mathematical logic*, *proof theory* and *type theory*.

LLMs, ATPs, and IPAs, all fall under the AI umbrella

- All of these AI systems are capable of increasing the **efficiency** and **productivity** of mathematical practice — *if we are also aware of their limits*:

– **LLMs** (Large Language Models) :
e.g. *ChatGPT* , *Gemini* , *Claude* , . . .

– **ATPs** (Automated Theorem Provers) :
e.g. *E* , *Vampire* , *Z3* , . . .

– **IPAs** (Interactive Proof Assistants) :
e.g. *Lean* , *Rocq* (formerly *Coq*) , *Isabelle* , . . .

- Of the three families, **IPAs** are the most interactive, and **ATPs** are the least interactive, with their human users. **LLMs** are the only of the three families that are prone to *hallucinate* — *i.e.*, to produce seemingly plausible, but in fact false statements.

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NOTES for slide 14:

- These three families are quite different in kind, even though all three fall under the **AI umbrella**:

  - **ATPs** are fully automated: given a conjecture, they search for a proof with no human in the loop. They are sound (a certificate they return is a genuine proof) but the search may not terminate.
  - **IPAs** are human-guided and machine-checked: the human supplies the proof strategy (tactics), the kernel verifies every step against a small trusted core. Soundness is essentially as strong as the kernel itself.
  - **LLMs** are statistical pattern generators, *not* sound by construction. They are useful for suggesting proof sketches or searching for relevant lemmas, but their output requires independent verification – typically by an ATP or an IPA.

- This last point is important: an LLM's fluency should never be confused with a guarantee of correctness. LLMs are known to *hallucinate* — to produce seemingly plausible, but in fact false statements — and recent work argues this is a *structural* consequence of how such models are trained and evaluated, not merely a defect to be trained away with more or cleaner data. See *Why Language Models Hallucinate*.

Two Dimensions in the Interaction Between Math and AI

- LLMs do not "escape" mathematics: they are trained by mathematical optimization on mathematical representations of language.
- ATPs do not "replace" logic: they implement proof search in formal calculi.
- IPAs do not "replace" proof: they require explicit formal definitions, libraries, tactics, and human-readable organization.
- ***Hence, when AI systems are used to deal with a mathematical object of study, mathematics appears twice: once as the object of study (theorems, proofs, mathematical structures) and once as the machinery/methodology (optimization, formal systems, proof search algorithms). This doubling reveals that AI cannot escape mathematics — mathematics is both what we study and how we study it. Put differently, mathematics appears at both the object level and the meta level.***

References for further reading:

The Lean Mathematical Library

Formalising Perfectoid Spaces

A Survey on Deep Learning for Theorem Proving

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NOTES for slide 16:

Two points:

- ***What do I mean by "mathematics is at both the* object level *and the* meta level*?"*** If you are familiar with mathematical logic — for example, first-order logic — there is a similar distinction between the **object level** and the **meta level**. An example of a proof at the **object level** is a formal deduction from Peano's Axioms, using proof rules, that $1 + 3 = 4$. An example of a proof at the **meta level** is a rigorous argument that the proof rules satisfies a **completeness** theorem, *i.e.*, for every (first-order) statement φ which is true in the standard model of arithmetic, there is a formal deduction of φ from Peano's Axioms.

- The examples from **Lean** are particularly important for mathematicians. The **mathlib** paper describes a community-built mathematical library with classical mathematics, dependent type theory, automation, and social organization. The *perfectoid spaces* project showed that an IPA can handle sophisticated modern arithmetic geometry; it did not remove mathematicians from the process, but required them to make definitions, dependencies and proof obligations explicit.

Parts of Mathematics for Which AI Can & Cannot Help

- ***LLMs:*** useful for examples, summaries, reformulations, heuristic suggestions, and some problem solving.

  Risks with LLMs: plausible mathematical prose can still be false, incomplete, or based on missing hypotheses. This happens when LLMs are said to **hallucinate**.

- ***ATPs:*** powerful at proof search in well-specified formal problems, especially first-order or theory-rich fragments.

- ***IPAs:*** excellent at checking formal proofs and building reliable libraries, but require formalization work and near-constant interaction with their human users.

  Common limit for ATPs and IPAs: success depends on the problem having been **formalized**, *i.e.*, framed in a machine-usable representation.

References for further reading:

FrontierMath: A Benchmark for Evaluating Advanced Mathematical Reasoning in AI

Solving olympiad geometry without human demonstrations

AlphaGeometry: An Olympiad-level AI system for geometry

Vampire theorem prover

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NOTES for slide 18:

The division between **help** and **replacement** is crucial. LLMs can be very useful in mathematical practice: they can suggest examples, translate between registers, offer possible approaches, and sometimes solve problems. But mathematical reasoning is hypothesis-sensitive, notation-sensitive and definition-sensitive. A fluent output is not therefore a proof. The benchmarks in the article "*FrontierMath* . . ." were designed using original, expert-vetted problems in order to reduce data contamination; the authors reported that contemporary frontier models solved under two percent of the problems in the initial benchmarks. This is not a permanent barrier, but it is strong evidence against **replacement** claims.

Aesthetic Aspects of Math Beyond the Reach of AI

- Mathematicians judge proofs and concepts not only by correctness, but also by *clarity, depth, inevitability, economy, fruitfulness, surprise*, and more . . . .
- These judgments are not decorative: they influence which definitions are adopted, which proofs are taught, and which problems become central.
- **An ATP can prove a theorem; it does not explain why the theorem is true.**
- **An IPA can certify a proof; it does not tell us why the proof is “illuminating” or “insightful”.**
- **An LLM can produce explanations; it does not by itself create a community’s shared sense of what is worth understanding.**

References for further reading:

Aesthetic Considerations in Mathematics

Using the proof assistant Lean in undergraduate mathematics classrooms

Reflecting on beauty: the aesthetics of mathematical discovery

Do Mathematicians Agree about Mathematical Beauty?

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NOTES for slide 20:

The claim here is not that machines can never optimize for formal proxies of elegance, shortness or simplicity. The claim is weaker and, for this lecture, more important: mathematical aesthetics is embedded in human practices of selection, exposition, teaching and community judgment. Work on the aesthetics of mathematics — such as in the reference by Natalie Sinclair "*Aesthetic Considerations in Mathematics*" — discussion of aesthetics and empirical work on mathematical beauty, supports the idea that aesthetic evaluation is part of how mathematics develops, not merely a private afterthought after correctness has been settled.

For a Human-Centered View of Mathematics

. . . and against an ***instrumentalist / utilitarian view*** of mathematicians as merely producers of theorems, ***replaceable*** once machines can produce the same results.

- The ***instrumentalist / utilitarian view*** is amplified by the rhetoric of the high-tech tycoons who measure intellectual work by *speed*, *scale*, *automation* — and *profits*.
- But mathematical practice also includes *posing problems*, *selecting definitions*, *judging explanations*, *refereeing*, *maintaining trust*, *repairing errors*, *teaching*, *passing techniques from one generation of mathematicians to the next*, and a lot more. ***The mathematics profession is a human institution***.
- The relevant question is therefore not: **"Can AI output theorems?"**
- The better question is: **"Under what human direction can AI improve mathematical practice without degrading human control and human understanding?"**

References for further reading:

Knowledge Collapse by Michael Harris,

Leiden Declaration.

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- In the article by Michael Harris, he warns that the AI industry's pursuit of Artificial General Intelligence (AGI) risks warping mathematics — a field historically experienced, since ancient times, as joyful for the mathematician and joyous when practiced and shared with others in the profession — into a commercial, machine-driven enterprise. He stresses why ***understanding*** matters and how ***formalization*** alone cannot capture a proof's role — hence, if the latter are ignored, we face the risk of "*knowledge collapse*".
- The *Leiden Declaration* provides the institutional and ethical framework: Concrete recommendations for defending human-centered practice across individuals, organizations, funders, and industry.

For a Human-Centered View of Mathematics

- For practicing mathematicians — even when they have not explicitly articulated this view — proofs are not merely cranks for churning out theorems. Proofs are also means for developing ***insight***, illuminating or redirecting ***intuition***, and deepening ***understanding***.
- A proof therefore has two distinct functions: ***(1) to certify a claim is true*** and ***(2) to help explain why it is true***. When a result is only used as a lemma, assurance of its validity may suffice; when the result itself is the object of interest, we also want to understand it.
- These two functions should not be confused. We often rely on ***lemmas we trust but whose proofs we do not fully understand***; moreover, certifying validity of a result or a theorem does not necessarily imply ***understanding it and its wider consequences***.
- Hence, the relevant distinction is ***not*** between ***proofs produced by humans*** and ***proofs produced by AI***. It sometimes happens that human proofs are opaque and that AI-produced proofs lead to new insights. What matters is whether proofs can be verified and — going beyond — whether they also help humans to understand.
- AI systems should therefore be welcomed as ***proof assistants***, especially for *calculation*, *search*, *translation*, and *formal verification*, thus enabling mathematicians to concentrate on ***understanding*** mathematical ideas and ***formulating*** new questions.

Reference for further reading:

On the current debate about AI replacing Mathematicians by Oded Goldreich.

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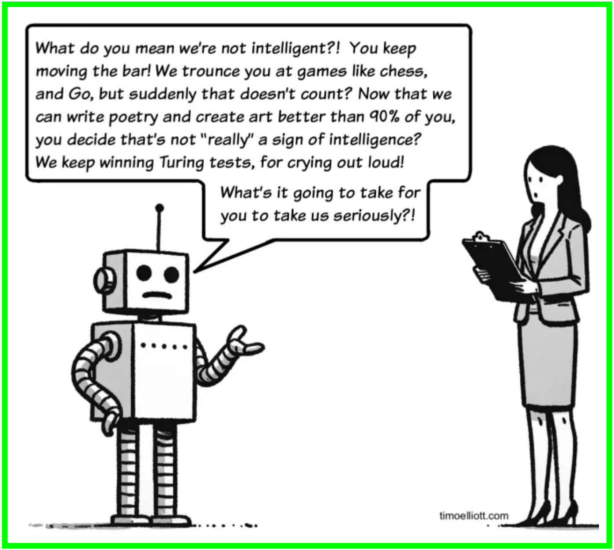
AI robots can produce theorems —
but can / should they do it without human probing and guidance ?



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NOTES for slide 25:

- True, mathematicians will increasingly work with AI systems that *suggest*, *search*, *translate*, *check* and *formalize*.
- But the decisive acts must remain human-centered: formulate the problem, choose the formalism, judge the explanation, and decide what counts as progress.
- The profession's future is therefore **not replacement**, but ***adaptation and reconfiguration***.
- The real risk is not mathematical obsolescence — it is institutional misreading by funders and policy-makers. Their main interests are profits; they will speak of financial sustainability or some such. And they will confuse, knowingly or not, ***adaptation / reconfiguration*** of tasks with ***replacement*** of a discipline.

Part II

AI and Mathematics: A Chronological Perspective

In an article Michael Atiyah first wrote in 1984, then adjusted in 2014, he deplored that "30 years of computer growth now threaten mathematics to its core," because, as he wrote later in the article:

"Whereas the eighteenth and nineteenth centuries witnessed the gradual replacement of manual labour by machines, the late twentieth-century is seeing the mechanization of intellectual activities. ***It is the brain rather than the hand that is now being made redundant.*** *This means that the challenge which we face is of quite a different order and analogies with the past may therefore be misleading" [emphasis in the original].*

Digression: Analogy with Evolving Modes of Locomotion

- **Locomotion** = "*act, ability, or power of moving from one place to another*"
- ***Did bicycling make walking obsolete?*** NO!
- ***Did motorcycles make bicycles obsolete?*** NO!
- ***Did automobiles make bicycles and motorcycles obsolete?*** NO!
- ***Did electric bullet trains make automobiles obsolete?*** NO!
- ***WHAT CONCLUSION SHALL WE DRAW FROM THIS HISTORY?***
- **Technological advancement does NOT imply technological replacement — and more, it implies adaptation of earlier modes of locomotion to new purposes.**

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- **Technological advancement does NOT imply technological replacement — and more, it implies adaptation of earlier modes of locomotion to new purposes.**

SKIP THE NOTES
Back to ToC

Digression: Analogy with Evolving Modes of Locomotion

- **Locomotion** = "*act, ability, or power of moving from one place to another*"

- ***Did bicycling make walking obsolete?*** **NO!**
- ***Did motorcycles make bicycles obsolete?*** **NO!**
- ***Did automobiles make bicycles and motorcycles obsolete?*** **NO!**
- ***Did electric bullet trains make automobiles obsolete?*** **NO!**

- ***WHAT CONCLUSION SHALL WE DRAW FROM THIS HISTORY?***

- **Technological advancement does NOT imply technological replacement — and more, it implies adaptation of earlier modes of locomotion to new purposes.**

SKIP THE NOTES Back to ToC

NOTES for slide 34:

Not Replacement, but Adaptation

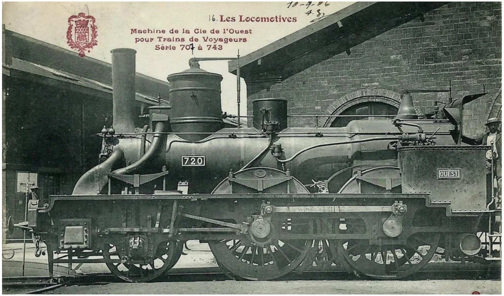
- Older modes ***adapt*** and ***evolve***.
- Walking didn't disappear — it adapted to urban recreation, exercise, and accessibility.
- Bicycles became urban commuting tools and leisure equipment — and used in new sports: ***one-day road races*** started in the 1890s, ***multi-day stage races*** started in the early 1900s (*Tour de France* was first held in 1903, *Giro d'Italia* was first held in 1909, *Vuelta a Espana* was first held in 1911).
- And other new sports were created based on other modes of locomotion, going beyond their utility for transportation and travel: ***motorcycle races***, ***auto racing***, ***sailplane soaring***, etc.

Digression: Analogy with Evolving Modes of Locomotion

- ***And catastrophes can happen on the way of evolving human inventions!***
-

Digression: Analogy with Evolving Modes of Locomotion

- ***And catastrophes can happen on the way of evolving human inventions!***
- **Example:** ***an advanced locomotive in the 1880s before a spectacular crash:***



Digression: Analogy with Evolving Modes of Locomotion

- ***And catastrophes can happen on the way of evolving human inventions!***
- . . . ***with far-reaching consequences for railroad safety after the crash:***

SKIP THE NOTES Back to ToC

NOTES for slide 37:

The 1895 Gare Montparnasse Derailment

On October 22, 1895, the Granville–Paris Express overran the terminal at Gare Montparnasse, crashing through a two-foot-thick stone wall and plunging 33 feet onto the street below. While the locomotive was completely destroyed and a pedestrian was tragically killed by falling masonry, the passenger carriages remained securely on the platform, sparing all 131 passengers on board.

NOTES for slide 37:

Causes of the Accident

The disaster resulted from a perfect storm of human error, scheduling pressures, and technical over-reliance:

- **Excessive Speed:** Running approximately seven minutes late, the engineer entered the terminal station at an unsafe cruising speed of 40 to 60 km/h (25 to 37 mph) in a reckless effort to recover lost time.
- **Brake Failure and Late Application:** The engineer relied entirely on the train's newly adopted Westinghouse automatic air brakes. When applied too late, they either suffered a sudden pneumatic pipe rupture or simply lacked the stopping power to counteract the train's massive momentum.
- **Crew Distraction:** Preoccupied with filling out overdue administrative paperwork, the conductor failed to notice the excessive speed and did not engage the emergency handbrakes in the rear carriages.
- **Regulatory Defiance:** Safety guidelines explicitly required trains to approach terminals using only manual brakes as a safety buffer, but drivers routinely ignored this rule to maintain tight timetables.

NOTES for slide 37:

Infrastructure and Safety Improvements

The accident did not alter the internal mechanics of steam engines, but it completely revolutionized railway safety technology and terminal infrastructure:

- **Dynamic Buffer Stops:** Before 1895, terminal tracks ended in weak, static barriers. Following the crash, engineers developed hydraulic and friction buffer stops that utilize heavy pistons or sliding jaws to progressively absorb and dissipate a runaway train's kinetic energy.
- **Braking Redundancy:** The crash mandated rigorous pre-departure air brake testing and strictly enforced the mandatory use of backup manual mechanical brakes during station approaches.
- **Operational Overhauls:** Conductors were banned from performing administrative tasks during critical transit windows. Additionally, track signaling was reconfigured to force strict terminal speed reductions long before platforms were reached.

Legacy: The disaster transformed rail transport by replacing an over-reliance on human vigilance with standardized mechanical and structural redundancies.

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- ***Did blackboards make books obsolete?*** **NO!**
- ***Did journals make lectures obsolete?*** **NO!**
- ***Did TEX and PDFs make handwritten math obsolete?*** **NO!**
- ***Did online videos make classroom teaching obsolete?*** **NO!**
- ***WHAT CONCLUSION SHALL WE DRAW FROM THIS HISTORY?***

  WILL AI SYSTEMS — LLMs, ATPs, IPAs AND OTHER SYSTEMS —

  MAKE READING / TEACHING / WRITING IN MATH OBSOLETE?

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NOTES for slide 44:

Evolving Modes of Reading/Teaching/Writing in Math:

- Math was first learned by listening, watching, and drawing — that was the way in which math was first practiced in ancient Greece, written texts (on parchment and papyrus) became crucial at a later time, from the Classical period of ancient Greece onward.
- Manuscripts and books allowed mathematical ideas to travel farther.
- Journals and monographs created specialized math communities.
- $\TeX$, PDFs, and online archives accelerated math writing and circulation.
- Videos and interactive notebooks changed how students encounter math.
- AI now makes math exposition conversational and instantly rewritable.

But Older Modes Remain Essential:

- Students still need to read slowly.
- Teachers still need to diagnose misunderstanding.
- Mathematicians still need to write definitions carefully.
- Diagrams, examples, and informal explanations still matter.
- Blackboard teaching still exposes the rhythm of mathematical thought.
- Handwritten work still reveals where understanding breaks down.

New Powers, New Risks — especially with LLMs

- LLMs can explain too quickly, before the student has struggled.
- LLMs can summarize without understanding what is central.
- LLMs can produce plausible but misleading explanations.
- LLMs can conceal differences between reading a text and sending a digest of it.
- ***LLMs can hallucinate*** . . . .

Needed Safeguards:

- Check definitions, hypotheses, and notation against the source.
- Ask students to explain ideas in their own words, verbally if possible.
- Preserve slow exercises, blackboard derivations, and written solutions.
- Use LLMs as translators and assistants – not as a final authority.
- ***"Verify, Don't Trust !"***

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AI Needs Mathematicians & Cannot Put Them Out of Work

Concluding the parallel between the evolution of* locomotion *and the evolution of* mathematics*:

- ***Walking and other human-body movements and gestures are to* locomotion *what human-paced reading, hand writing, and deliberate unhurried reasoning and reflecting are to* mathematics*.***

- ***No later mode eliminates the original modes. Every later mode is an extension of the original modes that changes their conditions of operation — to accelerate their productivity, to increase their efficiency, to protect them from newly induced harms.***

- ***But every new mode is also an extension that depends on the original modes to initiate, to direct, and to stop and restart its action — on human decisions.***

Back to ToC

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Back to ToC

Coda: What if . . . ?

Rather than learn how to solve that problem,
is it not better that we learn how to operate software that can solve it?

My Answer . . .

In the real world, mathematical scientists increasingly rely on AI to do the grunt work. That's perfectly fine. But here's the catch: ***AI systems are power-multipliers, and multiplying by zero — e.g., an ignorant user or a child — is still zero.***

My Answer . . .

In the real world, mathematical scientists increasingly rely on AI to do the grunt work. That's perfectly fine. But here's the catch: ***AI systems are power-multipliers, and multiplying by zero — e.g., an ignorant user or a child — is still zero.***

If you don't understand the math behind the problem you want to solve with AI, two things will happen:

- ***You will not know how to prompt the AI system.*** You cannot ask an AI system to solve a problem and then interactively engage it, if you don't understand the variables and relationships involved in the first place.
- ***You will not know when the AI system is hallucinating.*** In the case of LLMs in particular, they often make mistakes, which they present with absolute confidence and apparent sophistication. Without mathematical understanding to realize that an answer is off by a factor of (say) ten, you will end up publishing a broken report or returning a wrong result.

My Answer . . .

In the real world, mathematical scientists increasingly rely on AI to do the grunt work. That's perfectly fine. But here's the catch: ***AI systems are power-multipliers, and multiplying by zero — e.g., an ignorant user or a child — is still zero.***

We are not learning this math to turn ourselves into better ***human calculators*** — ***electronic computers*** won that race decades ago. *Just like the **electric bullet trains** that we invented, they won the locomotion race over us — **two-legged walkers** — decades ago.*

We are training our brains' logical muscles so that we can be the coordinators directing the AI systems, rather than merely copying and pasting answers we don't understand — answers that are often wrong anyway. ***We want to remain in charge of the AI systems we create and continue to develop.***

Thank you!

Back to ToC

This whole deck of slides can be downloaded from my academic homepage

— Assaf Kfoury —

search for, and click on, ***"Will AI Put Mathematicians Out of Work?"***