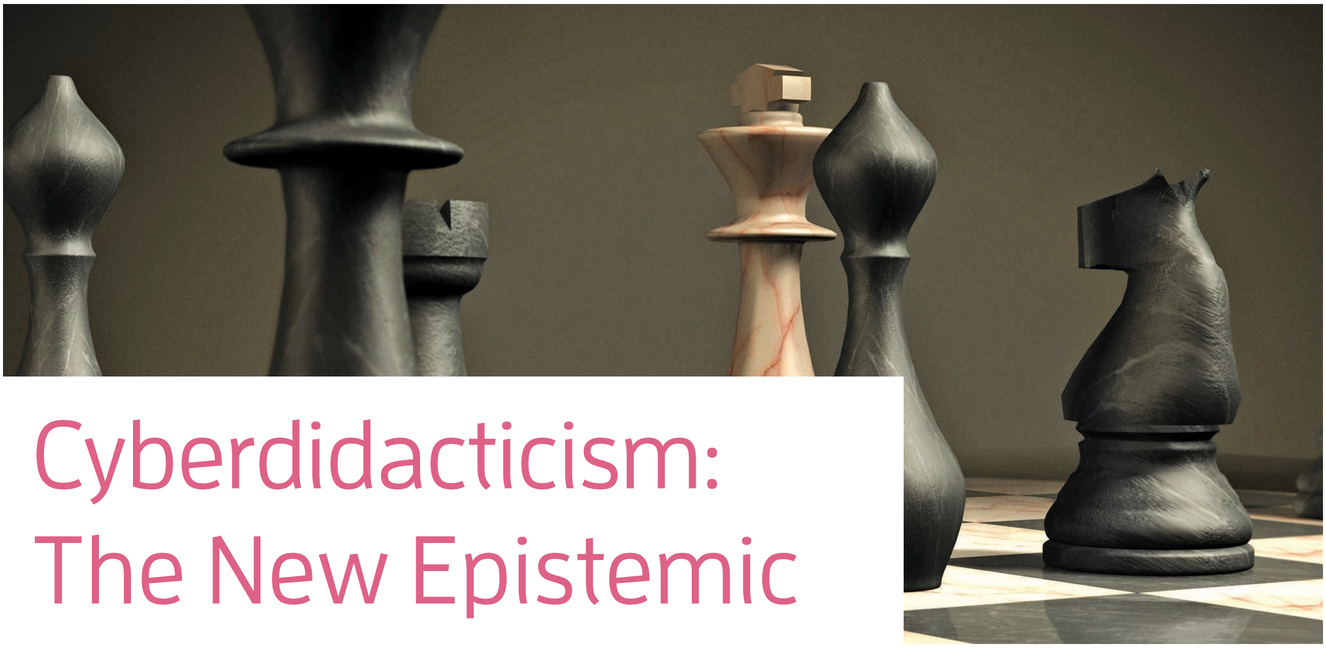

Cyberdidacticism: The New Epistemic Paradigm for Cognitive Minimalism and Generative Artificial Intelligence

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We postulate that generative artificial intelligence provides a new paradigm for disruptive technologies by enabling a community of cyberdidacts.

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Educators have always been fascinated by, and enamored of, autodidacts. There's just something inherently uplifting about individuals who can master subjects on their own. For bright, passionate, self-motivated students driven by insatiable curiosity, autodidacticism is an ideal complement to formal education. It might be an adequate replacement for traditional education in such cases were it not for the fact that its viability is highly dependent on so many external factors: environment, social circumstance, access to resources, opportunities, individual personality, genetics, etc. Further, a pseudoautodidacticism in the hands of the parochial and illiberal can quickly be driven off the rails by ideological biases and prejudice. So, while autodidacticism may not be an optimal learning environment for many, if not most, students, it is optimal for some students and refreshing for a teacher to witness.

With autodidacticism, a teacher is primarily a facilitator—someone

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who identifies and provides access to resources, identifies alternative educational pathways, makes recommendations based on experience, and, above all, avoids impeding the student's progress. In this sense, the teacher is somewhat akin to a crew coxswain: useful for direction but accounting for little of the expended effort.

LEARNING AND PERSONALITY

Psychological models of human personality identify at least a half dozen or so primary traits within human personality inventories. The Big Five[1,2] and Revised NEO[3] models list some variation of these five traits: conscientiousness, agreeableness, extroversion/introversion, openness to experience, and emotional stability, while other models add to this list (for example, the HEXACO model adds a sixth: honesty–humility[4]). Psychologists have been exploring the relationship between personality traits and other human characteristics for some time. Of particular interest here is the relationship between personality traits and personal values[5] and between personality traits and academic performance.[6]

Albert Bandura's notion of self-efficacy is a pivotal concept in this regard.[7] Bandura considers self-efficacy to be an individual's confidence in his/her ability to successfully complete a task. We note that self-efficacy is a perception or feeling that is experientially acquired by individuals and thus is both positively and negatively reinforced by actual successes and failures. Self-efficacy is both transferable to similar situations and also generalizable to new situations that are different from those already experienced. Self-efficacy may also be vicarious based on the observation of others. On Bandura's account, over time, an increase (decrease) of self-efficacy produces a confidence (apprehension) when faced with new challenges. But, as Bandura cautions, "analysis of how perceived self-efficacy influences performance is not meant to imply that expectation is the sole determinant of behavior. *Expectation alone will not produce desired performance if the component capabilities are lacking* (italics added)."[7] Hold that thought. We will return to this topic later, when we show how harmful it is when inflated self-efficacy becomes a surrogate for critical capabilities, such as reasoning proficiency, knowledge, and understanding, leading to a deluded self-efficacy.

SELF-EFFICACY AND INTERACTION

Bandura's explanation that self-efficacy is a function of "experienced mastery" places it squarely within the scope of informatics[8]—the discipline that Robin Milner calls the science of interactive systems and that many consider to be the nexus of technology, domain knowledge, and people.[9] That is, the process by means of which self-efficacy is achieved, the experienced mastery if you will, circumscribes a general-purpose, interactive learning system with multisourced and many-directional information stimuli, memory, a cognitive framework, feedback mechanisms, recognizers and analyzers of verbal and nonverbal patterns, and so forth. This is what Milner calls "conceptual armoury." There is an analogy between the acquisition of self-efficacy and what computer scientists call interactivity.[10] We may draw parallels between psychology and computer science descriptors as in such pairings as individuals/objects, stimuli/input, response/output, thoughts/processes, behavior/outcome, and so forth, as functionally similar pairs of elements that comprise complex systems that process and react to symbolic information in different domains. There is also a parallel between what psychologists call observational learning and what computer scientists call interactive computing. And strong cases can be made that both are nonalgorithmic since they may involve external, dynamic, interactive, or reactive events that take place concurrently with, but independent of, any ongoing processing.[10,11] Interactivity worthy of the name must accommodate inherently unpredictable responses to unanticipated external stimuli that is governed by possibly incomprehensible (at least, at the time) external influences. Letting a toddler play with a cell phone or mobile device or letting a blindfolded child drive a car are two primitive illustrations of the potentially unpredictable, nonalgorithmic nature of interactivity. Interactivity is a property of a truly open system. Human cognition is such a system: constrained in some ways, goal-directed and motivated in others, but nonetheless always open to new and unforeseen cognitive threads.

EFFICACY AND OUTCOME EXPECTANCY

Bandura draws an important distinction between outcome expectancy and efficacy expectation.

> "An outcome expectancy is defined as a person's estimate that a given behavior will lead to certain outcomes. An efficacy expectation is the conviction that one can successfully execute the behavior required to produce the outcomes. Outcome and efficacy expectations are differentiated, because individuals can believe that a particular course of action will produce certain outcomes, but if they entertain serious doubts about whether they can perform the necessary activities such information does not influence their behavior."[7]

This difference is subtle but critical to the hypothesis we will soon advance. Note that an irrational inflation of efficacy expectation may have undesirable social consequences, perhaps by overconfident bridge designers (for example, the designers of the Tacoma Narrows Bridge), the construction of poorly thought-through irrigation canals (resulting in the Salton Sea), the circumvention of U.S. Food and Drug Administration guidelines in the use of dangerous pharmaceuticals (for example, thalidomide), the failure to anticipate that some metals can rust and may not withstand heat (for example, those used in Takata airbags), that blowout preventers may not work well under high pressure (as in the BP Deepwater Horizon oil spill), the failure to admit that saying that a medical technology will work won't make it so (as in the case of Theranos), and so forth. Examples such as these led me to propose Gresham's twist on Moore's law: the world's capacity to create absurd technology doubles every 18 months.[12]

I'm endorsing what I consider to be a modest and uncontroversial claim: unjustifiably high efficacy expectations can have dangerous social consequences and justify continued vigilance. Further, the potential for danger is proportional to the lack of justification. For the sake of simplicity, and given that we're not conducting a research study in the social sciences, we may place my endorsement into more familiar, if pedestrian, terms: delusional overconfidence is undesirable and should be avoided. In fact, a healthy skepticism is always warranted— especially when it comes to technology.[13] Further, any technology that facilitates or encourages delusional overconfidence is prima facie objectionable, and its use should be discouraged.

CYBERDIDACTICISM

I'm suggesting that unbridled overconfidence is likely undesirable and shouldn't be encouraged without strong reservation. The widespread popularity of the "fake it 'til you make it" and "move fast and break things" aphorisms has to be taken with a large grain of salt: they have limited utility and, as time has shown, are all too often coincident with negative externalities. These aphorisms are serviceable components of a "feel good" approach to management: while they may upload the spirit and make the participants feel good about themselves and their activities, their vagueness is quickly seen to hide intellectual confusion or camouflage a technological immaturity.

From my perspective as an educator, there is substantial anecdotal evidence that generative artificial intelligence (AI) falls within the scope of these aphorisms. In terms of the preceding discussion, it unjustifiably inflates the "efficacy expectations" of typical users. This anecdotal evidence derives in part from the observed disparity between generative AI-produced homework and programming assignments on the one hand and exam scores and student interviews on the other—a level of disparity that was not observed to the same degree before generative AI use became commonplace in higher education. Of course, an anecdotal correlation is by no means proof of causation, but it does suggest a worthy topic for further study by social scientists. My intuition as a teacher tells me that a study somewhat analogous to the work of Bandura will reveal a strong connection between the reliance on generative AI and sundry behavioral affectations, such as inflated efficacy expectations, unjustified self-confidence, overreliance on the volume of output, suboptimal decision making, etc. That said, it is my intention here to explain the basis for my intuition as an educational observer and not a social scientist. I've observed the emergence of a new class of student, the cyberdidact, which for all intents and purposes may be considered an antithesis of the time-honored autodidact. It may be useful to draw some comparisons between the two.

Autodidacts derive considerable satisfaction from an ability to solve problems, achieve understanding, acquire mastery, etc., by themselves. Not in isolation, mind you, for inspiration is drawn from a variety of their own experiences, but without any formal instruction, motivation, or direction by others. To be sure, such self-learning is not without risk and not to be recommended for everyone. But when it works, autodidactism can avoid inefficiencies and distractions in traditional, compulsory mass education and may lead to remarkable results.

By contrast, a cyberdidact has a consumer-based, transactional approach to learning and problem solving and only a casual, incurious interest in understanding and mastery. On the cyberdidact's account, there is nothing particularly satisfying in the personal quest for knowledge but only in the apparent production of serviceable output. Indeed, that is the allure of generative AI: it provides an epiphanic-like endorphin rush with minimal cognitive investment. In this way, it is akin to interactive video games—but with the additional advantage of requiring less continuous interaction in order to achieve satisfying results. Armed with queries like "how many Rs are in strawberry?"[14] or instructions like "write a Python program to find prime factors for a set of integers," the cyberdidact's cognitive investment is complete—irrespective, mind you, of whether he/she fully comprehends the significance of the queries. To illustrate, what do the "strawberry" query and response tell the user–typist about the role of tokenization in large language models, the discordance between phonology and orthography, or the difference between orthography and semantics? How much of an understanding about number theory and factorization is required to create the program directive? In traditional intelligence, curiosity is the starting point of a creative process. With generative AI, curiosity is the end of the process.

TYPUS ERGO SCIO

An infatuation with generative AI lies in the superficial appeal of the end product embellished by the most cherished companions of a cognitive miser: intellectual economy and immediate gratification. But this intellectual parsimoniousness comes at a price. By deferring the majority of the cognitive heavy lifting to the generative AI tool, the user skirts the most fundamental components of metacognition: introspection, contextualization, reflection, reasoning, and the like. The ancient Greeks would describe generative AI as *nous*-less. What is more, this *nous-lessness* provides a fertile breeding ground for the propagation of cognitive biases, selective perception, cognitive dissonance, conspiracy theories, fake news, alternative facts, and sundry other pitfalls of inattentive and unprepared minds. The delusion behind the use of generative AI may be expressed by this corruption of Descartes' dictum: typus ergo scio (I type therefore I understand). With many audiences, the appeal of generative AI at this point seems to be presentation and optics over understanding and substance. Generative AI is more of a digital dilettante than an online oracle.

Because reasoning involves more than information retrieval, pattern recognition, and reaction, cognitive frugality carries with it a heavy cost. It understates the critical relationship of consciousness, understanding, and formal and informal logic to cognition, and it completely ignores the roles of self-correction, self-analysis, and self-criticism. A first principle of cognition is recognizing the substance and significance of an event. This requires more of us than the ability to produce an executable query. In very narrowly focused applications where such considerations are ancillary, such as may arise in automated theorem proving, calculation, pattern recognition, information retrieval, etc., generative AI is likely to be of considerable assistance to a scholar. But it is no substitute for human cognition: it may help in performing calculation, but it remains silent on why a calculation is important in the first place.

THE CYBERDIDACTIC HYPOTHESIS AND THE ONLINE DOPPELGÄNGER THOUGHT EXPERIMENT

We suggest the following hypothesis in light of our observations.

> The Cyberdidact Hypothesis: To the extent that it makes sense to correlate personality traits with academic performance, academic performance will not correlate with frequent use of, or reliance on, generative AI.

Potential corollaries: 1) those personality traits that correlate positively with cyberdidacticism are likely to correlate negatively with autodidacticism, vice versa; 2) the appeal of generative AI is inversely related to erudition; 3) generative AI is likely to lead to an unjustified, elevated self-efficacy; and 4) generative AI as a learning tool is demonstrably suboptimal. Why might this be?

We begin with Bandura's cautionary observation that "Expectation alone will not produce desired performance if the component capabilities are lacking." Self-efficacy is not a sufficient condition for academic or scholarly ability. Self-deception may also be at work. Self-efficacy is conditioned by internal and external feedback. Were one to see that certain patterns of behavior continually return high marks on exams, positive recognition from knowledgeable, respected peers, continued success in the exercise of skills, etc., one might legitimately assume some degree of self-efficacy. But, can we imagine a situation where the continuous feedback might be misleading?

Indeed, we can. Consider the case of a Loyal Online Doppelgänger— a loyal, reliable, expert online surrogate who can be counted on to take exams for you, interact with peers on your behalf, and perform your job—all via online communication systems where identity is electronically spoofed. Assume that the feedback on the doppelgänger's performance evaluations (in your name, of course) is consistently positive. But only you know of the existence of the doppelgänger, who, by assumption, will never disclose the ruse. Over time, how would the consistent, positive assessment of the doppelgänger's performance effect your self-efficacy? Remember that self-efficacy is conditioned by both internal and external feedback, but in this case all of the external feedback about your (the doppelgänger's) performance is strongly positive, but misdirected. My suggestion—which is confirmable or refutable by studies conducted by social scientists—is that self-delusion is an inevitable consequence and that, over time, a person's self-efficacy will unjustifiably increase despite the ruse and that this false sense of accomplishment will lead an individual to overconfidence, which will, in turn, lead that person to take on challenges for which he/she is underqualified. Our hypothesis predicts that a provable connection between our Loyal Online Doppelgänger thought experiment and the actual use of generative AI is obvious.

I further buttress my hypothesis by reference to the "Big 5 Model" (also known as the OCEAN model) of personality traits of basic psychology. For the present purposes, we'll use the definitions found on an online resource provided by the Harvard Graduate School of Education because it allows the online user to drill into arbitrary levels of detail and provides key references.[15]

1. *Conscientiousness*: The tendency to be organized, responsible, and hardworking
2. *Agreeableness*: The tendency to act in a cooperative, unselfish manner
3. *Neuroticism*: Emotional stability is predictability and consistency in emotional reactions, with absence of rapid mood changes. Neuroticism is a chronic level of emotional instability and proneness to psychological distress
4. *Openness to experience*: The tendency to be open to new

aesthetic, cultural, or intellectual experiences

5. *Extraversion*: An orientation of one's interests and energies toward the outer world of people and things rather than the inner world of subjective experience; characterized by positive affect and sociability.

Caveats are called for. First, models of personality types are instruments of social science, not computer science; so, my analysis represents an oversimplified discussion of the topic. Second, there is no universal agreement on which personality traits belong in the Big Five and what precise definitions should be used to describe them. Third, there is nothing that compels us to use the number 5—social scientists have used as few as two and as many as 20 traits.[16] Fourth, there are several different approaches to identifying relevant personality traits. I am neither a social scientist nor an expert on personality theory, but since I am advancing a hypothesis and not a proof, some brevity and occasional appeal to hand waving should be tolerable.

Social science research on the relationship between personality traits and self-efficacy has been conducted. In particular, the predictive powers of the Big 5 and self-efficacy on academic performance are well documented. The following paragraphs report the observed relationship between the Big 5 personality traits on the one hand and academic performance and self-efficacy on the other.[6]

> "Research shows that the Big Five traits relate to academic performance. Conscientiousness, that is, self-discipline, facilitates schoolwork by imparting preparedness. Openness, that is, imagination, helps with new modes of studying. Agreeableness, that is, compliance, increases consistency of class attendance. Extraversion, that is, sociability, hampers students' focus, and neuroticism, that is, emotional instability, is associated with test anxiety, where both traits hinder performance. Empirical support for the predictiveness of some traits is stronger than for others. For instance, 'Conscientiousness is the most robust predictor of academic performance with an average correlation of .20. '"
>
> "Self-efficacy is correlated with academic performance .... A recent meta-analysis examined 50 antecedents of academic performance and found that self-efficacy had the strongest correlation ($r = 0.59$) .... In the same study, of the Big Five traits, only conscientiousness significantly correlated with performance ($r = 0.19$). In another synthesis, which examined 105 predictors, self-efficacy was the second (after peer assessment) strongest predictor of academic achievement...."

My hypothesis derives from my strong suspicion that social science research will show an inverse correlation between some of these Big 5 traits and eagerness to rely on generative AI for academic and scholarly pursuits. I challenge the readers to consider for themselves the degree to which personality traits such as conscientiousness, self-discipline, imagination, consistency of class attendance, etc., would correlate with the reliance of generative AI for scholarly insight. Similarly, one might consider whether *unjustifiably* high self-efficacy is likely to lead to quality academic or scholarly work. I can see how it might lead to increased productivity (via automation), but productivity in isolation is not a reliable indicator of the accuracy, value, or impact of scholarship. Particularly worrisome is the reliance on generative AI for the creation of programming source code—especially when used in critical systems. In fact, one would expect that more reliable contributors to quality academic or scholarly work might be a climate of self-doubt, skepticism, agnosticism, and aporia.

That said, at this point, our hypothesis should be understood within the framework of technology education rather than social science research. From what I can tell, most postsecondary educators with whom I work agree that this hypothesis is consistent with observation in the classroom. However, social science research places much higher demands on hypothesis validation than observation and anecdotage. It remains to be seen whether this hypothesis will receive validation in that realm.

From a computing perspective, generative AI is algorithmic; thinking is not so limited. There is a dimension of human thought that is inherently nonlinear, dynamic, and interactive. Peter Wegner makes the point that interactive computation is nonalgorithmic convincingly in several articles,[10,17] and one key element of his argument is that algorithms cannot process disparate input information that was not anticipated in its design. In Wegner's words[10]:

> "The radical notion that interactive systems are more powerful problem-solving engines than algorithms is the basis for a new paradigm for computing technology built around the unifying concept of interaction.... The paradigm shift from algorithms to interaction is a consequence of converging changes in system architecture, software engineering, and human-computer interface technology...."

What is more,

> "The irreducibility of interaction to algorithms enhances the intellectual legitimacy of computer science as a discipline distinct from mathematics and, by clarifying the nature of empirical models of computation, provides a technical rationale for calling computer science a science."

For additional details, the reader is encouraged to read Goldin, Smolka and Wegner.[11]

Wegner's argument implies that generative AI platforms, as algorithmic implementations of large language model neural nets, will never achieve parity with human thought. Such being the case, the use of generative AI algorithms can never prove to be an adequate substitute for human understanding.

CYBERDILETTANTISM

Again, our experience suggests that cyberdidacticism will hold out special appeal for cognitive misers characterized by lower academic standards, limited scholarly ability, unjustified overconfidence, indolence, etc. I emphasize once again that this does not imply that generative AI is without scholarly utility. Certainly, its use to jog memory, maximize information uptake, detect plagiarisms and forgeries, check facts, search databases, and review, debug, and document program code, and its aid in parsing, detecting plagiarism and copyright violations and authorship patterns, image recognition, language translation, modeling, address learning challenges, etc., are widely acknowledged. And if its use were restricted to such a support role in traditional learning environments, the potential downsides would be much shallower. However, when it is used as a surrogate for imagination, creativity, understanding, reasoning, etc., to create content, its overall social value comes into question. It is unfortunate that a large part of the appeal of generative AI in higher education seems to be that it provides a path of least resistance in the quest for measurable output and meeting deadlines. As such, it is a natural complement to social media for those who prefer presentation to substance, opinion to fact, belief over certainty, and approximation over accuracy, and are content to work with derivative and questionable content and to resolve problems with a minimum of critical reflection.

If left unchecked, generative AI cannot help but facilitate *cyberdilettantism* for those who are so inclined. If the goal is simply to generate plausible, token output, there is little incentive to go beyond a superficial understanding of a topic. It is the nature of the beast. Generative AI output justifies at best a participation trophy for the user who's minimally involved in the game.

A similar point was made in a recent article in the *Chronicle of Higher Education*:

> "Shriram Krishnamurthi, a computer science professor at Brown University, has noticed that as more high schools teach programming with wildly varying degrees of rigor, incoming students are increasingly showing up thinking they know more than they do. 'There's this weird thing where they are very competent at patching together some things and producing graphs that look nice,' Krishnamurthi said, 'but their understanding of what they did is pretty low.' (He added that he wasn't casting judgment on the individual winners at NeurIPS. 'There has always been and will always be a sliver of students that are extraordinarily capable,' he acknowledged. Outside of NeurIPS, high schoolers can pay companies a handsome fee[18] to coauthor academic papers, a cottage industry that's widely criticized."[19]

Of course, so-called paper mills have marketed bogus scholarship online for decades. This service is not limited to students. In a recent article in *Science*, Jeffrey Brainard reported that even "journals are awash in a rising tide of scientific manuscripts from paper mills - secretive businesses that allow researchers to pad their publication records by paying for fake papers or undeserved authorship."[20] Generative AI is becoming integral to the paper mill supply chain—by either allowing users to bypass the paper mill or allowing the paper mills to become more efficient. In either case, academic standards are undermined. In addition, the generative AI "paper mill" can create the illusion that the user has actually accomplished something. But, in the case of the "paper mill," there is no delusion about authorship. The purchaser knows full well that he/she has no cognitive investment in the effort. However, generative AI enables self-delusion, for the actual "author" is a computer, the paper is presumed unique, the process is anonymous, and there is no financial transaction recorded to betray the deception. Generative AI can be a form of scholarly chicanery on a desktop. Anyone with a computer and an Internet connection can become an immediate cyberdilettante.

THE ERA OF THE CYBERSAVANT

Generative AI provides access to computing power that usually isn't available to the general population. That would be a social good were it not for the fact that generative AI's appeal lies in the ability to use these platforms with

1. negligible cognitive investment
2. low or negative cognitive inertia
3. logical detachment from the underlying issues
4. a propensity for propagating bias and promoting agendas
5. a proclivity for disinformation with the potential consequence of producing an unjustified self-efficacy.

Therein lies the proverbial rub. Social scientists have studied the effect of inflated self-efficacy and overconfidence,[6] but they have not fully embraced the potential adverse effect of generative AI in the mix. We only partially understand the social effects of such technology-inspired self-delusion.[21]

Further, an overreliance on generative AI is but one of a number of current unhealthy trends in education. Its effects must be understood in the context of a broad decline in reading, a decline in foreign language programs, and the fact that scholarly materials are becoming less appealing to a general audience.[22] Humanities, liberal arts, and a diversified, well-rounded education have always been threatening to illiberal autocrats, dictators, and demagogues who focus on the development of compliant subjects and obedient workforces rather than a community of free thinkers who continuously challenge the existing order. So, selectively trained generative AI is a demagogue's dream. If our hypothesis is correct, the use of generative AI as a substitute for traditional scholarship is going to exacerbate many of our social–political ills. While society enjoys a very long history of deploying technology before fully understanding the negative externalities of its use, generative AI is unique in its ubiquity, ease of use, political implications, and potential for social disruption.

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