Yes—Money Makes Artificial Intelligence

In recent years, artificial intelligence has often been portrayed as the inevitable result of human knowledge and intellectual progress. However, this narrative obscures a crucial fact: money makes AI. From Cold War military laboratories to today's billion-dollar large language models, the development of AI has always relied on massive financial investment to exist, evolve, and exert influence. AI does not merely benefit from financial support—its very definition, direction, and deployment have been fundamentally shaped by money.

This paper argues that AI is not simply an academic or organic product of scientific discovery—it is a construct of state funding, corporate rivalry, and economic ambition. It explores how government agencies such as DARPA laid the foundations of AI through Cold War-era military investments; how modern breakthroughs like GPT-4 and Claude have only been made possible through high-cost compute infrastructure, massive datasets, and billion-dollar investments from corporate giants.; how data ownership and chip production have fostered new forms of "digital colonialism"; and how the logic of capital continues to reproduce social inequality under the guise of technological progress. While intelligence may be abstract, artificial intelligence concretely reflects who can afford to build it—and for what purposes.

The origins of artificial intelligence do not lie in private laboratories or tech startups, but in Cold War-era national strategies. In the 1960s, the U.S. Department of Defense established the Advanced Research Projects Agency (ARPA) which was later renamed DARPA to fund high-risk, high-reward research projects that could deliver military and strategic advantages. In fact, most computer projects of the 1940s and 1950s were either directly or indirectly funded by the U.S. military. By the 1960s, AI research remained heavily dependent on military support. ARPA's investment in AI exceeded the total funding from all other countries combined, with much of it directed toward institutions like MIT and Stanford—most notably through initiatives like Project MAC—which significantly contributed to the field's growth.(Haigh) Why do we say money makes AI? Because early AI researchers relied on large, expensive computers, research resources were highly concentrated in a few government-backed labs. Funding determined not only who could participate in AI research, but also which directions that research could take. Projects without clear commercial applications were entirely dependent on government support, and when policy priorities shifted or evaluation reports proved unfavorable, funding was quickly withdrawn—bringing progress to a halt. From the very beginning, AI's trajectory has been tightly bound to capital: without money, there can be no experiments, no computational power, and no sustainable advancement.

Although early government investment accelerated the development of the AI field, it also revealed that money is an indispensable part of AI research—something clearly demonstrated by the two so-called "AI winters." But what exactly is an AI winter? The term refers to periods when interest in and funding for artificial intelligence dropped significantly.The first AI winter was caused by a combination of factors, including funding cuts, overly high expectations, and the release of the ALPAC report in 1966, which concluded that machine translation research had not met its goals. The consequences were far-reaching: government agencies and private investors sharply reduced their support, many AI projects were canceled, and research activities slowed considerably. All of this underscored the crucial role of funding in sustaining AI research.The second AI winter occurred from the late 1980s to the mid-1990s. This downturn was largely due to the limitations of expert systems. These systems failed to meet commercial expectations, which led to a significant decline in investment and eventually triggered the second AI winter. (Cdteliot)These cycles demonstrate that AI is not a field driven solely by academic progress—it is deeply shaped by economic conditions. When funding dries up, the pace of innovation slows dramatically. The development of AI does not follow a smooth, linear trajectory; rather, it rises and falls in cycles, driven by the flow—and withdrawal—of money.

In the 21st century, the financial demands of cutting-edge AI development have reached unprecedented levels, making the field accessible only to governments and the wealthiest tech giants. For example, it has been reported that training a state-of-the-art language model like GPT-3 cost over $12 million in compute resources alone, while the total investment for models such as GPT-4 and Claude has reached into the hundreds of millions of dollars. OpenAI, which initially operated as a nonprofit organization committed to the safe and open development of artificial intelligence, found it increasingly difficult to sustain its operations due to the high costs involved. In 2019, it transitioned to a capped-profit structure, and in 2023, it secured a $10 billion strategic investment from Microsoft. (Wiggers) This shift reveals a core reality:

contemporary AI research is no longer merely an academic endeavor—it has become a highly capital-intensive industry. From data acquisition and GPU infrastructure to the massive electricity required for training, every stage demands substantial funding. As a result, only a handful of corporations with deep financial and technical resources are able to compete, effectively determining the direction of AI development. These entities decide what kinds of AI get built, who gets access to them, and for what purposes they are deployed. In such an ecosystem, money not only makes artificial intelligence—it defines the boundaries of what AI can be.

In today's AI landscape, data is no less valuable than money—or more precisely, it is money that enables access to data. Large-scale AI models depend not only on immense computational power but also on massive datasets, which are often collected through web scraping or platform-based monopolies. As a result, some scholars have referred to this phenomenon as "digital colonialism": technology companies headquartered in the Global North extract data from users in the Global South—without compensation, consent, or transparency.For instance, most large-scale pretrained language models have historically been built on datasets dominated by English-language content. In the case of non-code data in Chowdhery et al. (2022), approximately 78% was in English. Although Google's PaLM 2 model claims to have used a more multilingual and diverse pretraining mixture, English continues to dominate both model performance and training emphasis. (Mussgnug & Leonelli) The language distribution tables provided in the report further show that many Asian and African languages are still significantly underrepresented. This imbalance is far from fair. The companies that control data pipelines have disproportionate power to determine what AI learns, understands, and replicates.In this sense, data becomes a new form of capital, and the ability to acquire data becomes a key competitive advantage. As McKinsey has projected, generative AI could contribute $2.6 to $4.4 trillion annually to the global economy—but the majority of that value will be captured by a small number of companies that own the infrastructure and datasets. (McKinsey&Company)Money is required to obtain data, and data, in turn, generates more money—further reinforcing the reality that AI is inseparable from capital.

Although most AI projects rely heavily on corporate capital, forms of resistance have nonetheless emerged through open-source models, academic collaborations, and cultural alternatives. Projects such as Meta's LLaMA, France's Mistral, and BLOOM have attempted to make high-quality models accessible to the public by releasing model weights, source code, and training procedures. These efforts demonstrate that innovation does not always depend on billion-dollar budgets—ideas, collaboration, and shared values can also be powerful drivers of progress.（Knight) However, even these open-source initiatives face structural limitations. Many rely on pretrained models provided by tech giants or require access to high-end GPUs, which remain largely controlled by companies like NVIDIA or cloud platforms such as AWS and Google Cloud. On the cultural front, resistance has taken the form of critiques against Western-centric systems—for example, the development of the Chinese typewriter once symbolically and technically challenged the dominance of the QWERTY keyboard infrastructure.Yet without equitable access to hardware and sustainable funding, such efforts often struggle to scale. The paradox is clear: openness may expand the boundaries of participation, but it remains difficult to escape the gravitational pull of capital. True democratization of AI requires not only open code, but also equitable access to computation, data, and public funding mechanisms.

Behind the dazzling promise of AI lies a deeper ethical question: Who is AI really serving? In domains such as housing, healthcare, and social welfare, algorithms often use opaque, risk-based logic to sort people into categories of the "deserving" and "undeserving"—a process that disproportionately penalizes the poor and marginalized. This logic mirrors the broader economic structure of the AI industry: the benefits of automation are captured by large corporations, while its harms—job displacement, surveillance, and bias—fall mostly on vulnerable populations.Generative tools like DALL·E and Copilot are automating creative and professional labor, sparking intense debates over authorship, compensation, and professional ethics. Studies show that high-paying white-collar professions in law, media, and education are increasingly being disrupted by large language models—yet the workers in these sectors have little to no influence over how such models are trained or deployed. Meanwhile, the companies profiting from AI often obscure the sources of their training data and avoid public accountability. As a result, AI not only reflects existing economic inequalities—it actively replicates and amplifies them. The core ethical question is no longer whether machines can think, but who benefits when they do.

Artificial intelligence may be built on logic, models, and data—but its development has always been driven by capital. From Cold War defense budgets to trillion-dollar tech investments, from data extraction to compute monopolies, the story of AI is not merely one of innovation—it is one of capital accumulation. Although open-source movements and ethical debates offer limited resistance, they still operate within a system defined by financial gatekeeping. The future of AI, therefore, is not just a technological issue—it is a political one. If capital continues to determine which forms of intelligence get built, whose voices are amplified, and which problems are deemed worth solving, then AI will remain a mirror of existing power structures rather than a force that challenges them.The task ahead is not merely to make AI more powerful, but to make it more just. And that task begins with a fundamental question: Who gets to fund the future of intelligence—and who gets left behind?

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