Understanding Hype in Innovation: An Artificial Intelligence Case Study

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Sage Wibberley

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Advisor

MC Forelle, Department of Engineering and Society

I. Introduction

In recent years, we have seen the rise and fall of countless technologies that offer little more than distraction while consuming vast resources to do so, all at a time that demands careful attention on how these resources are managed. Consider NFTs, Cryptocurrencies, and the Metaverse as prime examples of this—solutions in search of a problem that are willing to keep data centers churning in a world that increasingly calls for climate mindfulness. New technologies must be developed responsibly, ensuring that finite resources are not overinvested and that goal-setting strategies are grounded in realistic expectations.

I argue that a key contributor to these short-sighted technological developments is public and corporate hype. A phenomenon in which the expectations surrounding a technology peak far above what that technology is capable of accomplishing. Drawing from Gartner's Hype Cycle, a framework describing the relationship between hype and technological yield, this is referred to as the peak of inflated expectations. At this point, a technology is likely to overpromise and underperform. By exploring the mechanisms through which hype acts, I hope to inspire an awareness of how it interacts with innovation and demystify the technologies it affects.

Corporate and consumer hype have created an environment that uses limited resources recklessly to pursue uncertain and oversold outcomes. To argue this, I will first conduct a literature review exploring Gartner's Hype Cycle, Sarewitz and Nelson's Three Rules for Technological Fixes, the interaction between economics and hype, and the dire climatic situation that irresponsible technologies threaten to exacerbate. First, a discussion of Gartner's Hype Cycle will describe what it is and how it operates, before contextualizing its drawbacks and how they affect the framework as a tool. Then, Sarewitz and Nelson's three rules will be defined and explored. Following this, the importance of climate management will be argued before demonstrating the interaction between economics and hype. When the literature review is complete, I will describe the methodology used in the analysis of this paper. Here, I describe building a case study on artificial intelligence (AI) and its interaction with hype using publishing data available through Google N-Grams and investment data from Our World in Data. The methodology section will also outline the use of Sarewitz and Nelson's rules. Analysis will begin by describing the history of AI and its transition into contemporary AI after the advent of deep learning. Data regarding AI hype will then be reviewed, and a case made for its presence. The repercussions of hype in AI will then be laid out. Sarewitz and Nelson's framework will then be applied to AI, both as a data management technology and a hype-defined technology. The conclusion will finally make a case for managing hype both within and beyond artificial intelligence, and explore how this is possible.

II. Literature Review

To understand how hype interacts with technology's development, we must first understand what hype is and how it works. The Gartner Hype Cycle is a tool used in business analysis—it describes how expectations surrounding a product evolve throughout its development. Gartner states that, while a budding technology progresses, it experiences a particular pattern of how it is perceived relative to what it can accomplish. Fenn and Linden (2003) state that hype cycles describe how new technologies often face a surge of inflated expectations, or 'hype', after a breakthrough, followed by a period of disillusionment and eventual stabilization as realistic outcomes become clear. Gartner's Hype Cycle examines this expected process using five unique stages of public expectations: the innovation trigger, peak of inflated expectations, trough of disillusionment, slope of enlightenment, and the plateau of productivity (Blosch & Fenn, 2018), see Figure 1.

- Innovation Trigger - Describes the start of the hype cycle, typically when a breakthrough or public demonstration occurs.
- Peak of Inflated Expectations - As a technology becomes widely recognized, the expectation of what the product will deliver becomes largely exaggerated. This can lead to investment bubbles and overstated outcomes.
- Trough of Disillusionment - As impatience outgrows excitement, expectations crash. This is generally brought on by slower-than-expected adoption and failures to immediately reach marketability.
- Slope of Enlightenment - As early adopters manage to make genuine progress, a renewed effort is placed into the technology's development. In this time, companies come to understand how the technology is best deployed and come to a more whole understanding of its strengths and weaknesses.
- Plateau of Productivity - As the real-world benefits of the technology are realized, individuals and companies come to understand how it can be effectively used. In this final stage, expectations come to align with the real value proposed by an innovation.

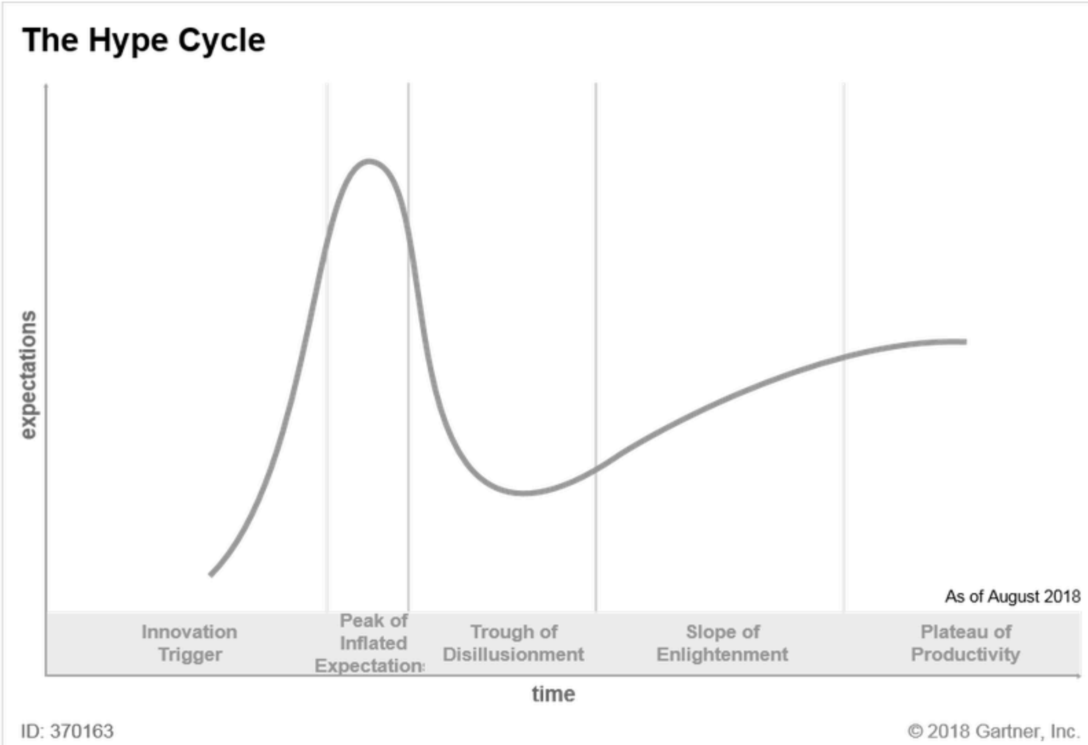

Figure 1. The Gartner Hype Cycle (Source: Blosch & Fenn, 2018)

While Gartner's Hype Cycle has found a long-term home in business consultancy, it is important to understand its limitations and the arguments of its detractors. Steinert and Leifer (2010) argue that the model lacks empirical evidence, relying on the assumption that technological development strictly follows an S-curve and that hype levels follow a similarly predictable pattern; very little mathematical and empirical evidence exists to corroborate these assertions. Furthermore, Gartner's Hype Cycle is often used to excuse the poor performance of recent technologies. Author and IT administrator, David Gerard (2019), explores this in a blog post, demonstrating that oftentimes, non-viable innovations are said to be stuck in the trough of disillusionment, when a more likely explanation is that some technologies will inevitably fail. Professor of STS at Virginia Tech, Lee Vinsel (2023), argues that hype is narrative-driven, with investment often derived from speculative expectations of a technology's return rather than practical predictions. Vinsel argues that hype often stems from investors' fear of missing out (FOMO), leading to excessive investment and unproductive speculation. While Hype Cycles are not without their flaws, and caution should be employed in not using them prescriptively, they provide a valuable language with which technological innovations can be discussed.

Sarewitz and Nelson's Three Rules for Technological Fixes (2008) provide a framework for understanding the shortcomings of technological solutions based on their interaction with the problems they aim to address. These three rules assess the effectiveness of a technology: the solution must embody the cause-effect relationship connecting problem to solution, the effects of the technological fix must be assessable using relatively unambiguous or uncontroversial criteria, and research and development must be most likely to contribute decisively to solving a social problem when it focuses on improving a standardized technical core that already exists. While Gartner's Hype Cycle provides a tool for understanding a technology's interaction with consumer and market expectations, applying Sarewitz and Nelson's Three Rules presents a shared basis for understanding its shortcomings and predicting its likelihood of success.

Climate change creates an environment that demands the careful balancing of technology; many contemporary solutions fail to consider meaningful timelines and practical fixes. Climate experts predict that only 7-8 years remain to implement effective mitigation strategies before irreversible damage occurs (Feigin et al., 2023). Failing this timeline will yield numerous catastrophic consequences to human life. Climate change risks human health, exacerbating weather-related outcomes such as heat stroke, air quality degradation, and increased disease transmission (Crimmins et al., 2016). Furthermore, the consequences of climate change will erode access to land and agriculture, exacerbating global food insecurity (Chandrasekhar et al., 2022). Under these circumstances, it is clear that action must be immediate and fruitful. Even still, technology continues to wreak havoc on carbon emissions—rare earth mineral extraction, blockchain utilization, and generative AI are but a few ongoing examples of extremely carbon-negative endeavors (Nayar, 2021; Truby et al., 2022; Kneese & Young, 2024).

Understanding the economic conditions surrounding hype is crucial to managing it; climate change has created economic structures that incentivize climate-first innovations, but these structures also hinder the timely and meaningful progress of solutions. Taalbi (2017), through empirical analysis of Swedish inventions throughout the third industrial revolution, demonstrates that innovation typically emerges as a result of creative solutions to arising problems or is spurred by technological opportunities. The ongoing climate crisis can be seen as an innovation catalyst, as evidenced by advancements in batteries, desalination, and many other energy and climate-related innovations (IEA, 2024; Amoudi & Voutchkov, 2021; Moscona & Sastry, 2022). While these economic structures can act as much-needed motivators, they also threaten to stand against progress. Basseches et al. (2022) explore how political structures and market-oriented governance create obstacles in the path to climate protection. Political structures and governmental decisions often operate around economic incentives, both affecting and being affected by them. A clear example of such blockages is fossil fuel lobbying, which becomes more prolific as a fossil fuel firm expects more risk of divestment due to climate relief efforts (Lantushenko & Schellhorn, 2023). Such lobbying efforts delay and detract from climate efforts by introducing deception and misinformation, manipulating democratic systems to serve industry interests, and undermining democratic functions and freedoms (Martinez et al. 2023). In her blog post, Lorien Pratt (2015) argues that companies use hype and overblown marketing to secure investment, which then creates a negative feedback loop as companies compete to promise more and more. Economic incentives and hype have a symbiotic role, creating feedback loops that serve to encourage one another. While these cycles of hype can encourage rapid growth, they can also cause excessive spending and waste, demonstrating a need for forethought in how technology is implemented.

III. Methods

To critically assess the role of hype in technologies, this paper applies Gartner's Hype Cycle and Sarewitz & Nelson's framework for technological fixes to analyze development cycles and the conditions for successful solutions, using artificial intelligence (AI) as a case study. I build a brief history of AI, disambiguating its often mystified definition before exploring contemporary AI developments to understand the surge of recent attention. Gartner's Hype Cycle is used to evaluate the "hype state" of AI based on its current stage of adoption and effectiveness. This analysis of hype is performed using publishing records from Google N-Grams, and data sourced from Quid's index report (2025) and the U.S. Bureau of Labor Statistics (2025) collated via Our World in Data (2025). Sarewitz & Nelson's Three Rules are then applied to artificial intelligence to understand where associated technologies succeed and where they fall short. This analysis is performed on contemporary AI as both a data management system and a construct of hype. The case study will then be used to draw broader conclusions regarding how to responsibly continue the development of new technologies, including a discussion surrounding potential pitfalls and how to manage hype.

IV. Analysis

The origin of AI can be traced to the origin of computing, both are developments of offloading labor that would usually be placed on human cognition onto circuitry and electrical systems. Thoughts of intelligence hosted within machines were kicked off by two seminal occurrences in the early 1940s, the authoring of Isaac Asimov's Runaround, which described three laws of robotics, a set of rules for the development of ethical intelligent machinery, and Alan Turring's successful implementation of The Bombe, a machine that would go on to crack the Enigma code used by the Nazis in WW2 (Haenlein & Kaplan, 2019). It wouldn't be until 1956 that the term "AI", or artificial intelligence, would be coined at the first conference held on the topic in Dartmouth, which would mark the first serious discussion of attempting to emulate human intelligence through machinery (Solomonoff, 2023). In 1966, MIT computer scientist Joseph Weizenbaum developed the first machine capable of communication through language, dubbed ELIZA (Weizenbaum, 1966). Throughout the 1970s, development would plateau as AI was limited by processing capabilities at the time, although small breakthroughs were made regarding imaging and efficiency (Shao et al., 2022). AI momentum was reestablished throughout the 1980s and 1990s with notable accomplishments including the introduction of non-monotonic logic (NML) more capable of complex reasoning (McDermott & Doyle, 1980) and Deep Blue's triumph over Gary Kasparov in chess in 1997 (Campbell et al., 2002), a feat long thought to be impossible by AI's detractors.

Until the late 1990s, AI operated on what are called "expert solutions", or a series of logics that are performed in a distinct attempt to emulate human intelligence through "if-then" statements, as if formally breaking down intelligence into a flowchart of decisions (Haenlein & Kaplan, 2019). Today's massive resurgence in research and an abundance of discussion surrounding AI was spurred by the development of deep learning (Shao et al., 2022). Deep learning describes a series of layered neural networks (the same kind that made up previous models), described as deep neural networks, to undergo unsupervised learning. This learning is accomplished using forward propagation and backpropagation to learn, correct, and reinforce the steps required to accomplish complex tasks in a computational structure not dissimilar to neurons within the animal brain (Holdsworth & Scapicchio, 2024). Modern developments within the field have created Convolutional Neural Networks (CNNs) capable of complex image processing, Recurrent Neural Networks (RNNs) that have advanced language processing, Autoencoders capable of generating original work (often called Generative AI), and many more (Holdsworth & Scapicchio, 2024). These advancements stemming from deep learning are often what people refer to when discussing AI today, and are what I will refer to as 'contemporary artificial intelligence'.

As deep learning has bolstered artificial intelligence research, so too has it placed discussion of AI into the public commons. With genuine advancements come inflated expectations and unrealistic desires for burgeoning technologies. This phenomenon, described by Gartner's Hype Cycle's inflated peak of expectations, I argue, is in full effect regarding AI. Throughout its lifetime, artificial intelligence has developed from a relatively obscure academic project to a full-grown contemporary movement, with technological fetishists, detractors, and everything in between. This massive uptick in relevance can be seen using Google N-Grams, which documents the publication frequency of user-specified terms. Figure 2 displays the publishing frequency results for "Artificial Intelligence" between 1950 and 2022. This graph displays the birth of the term following Dartmouth's 1956 conference, followed by steady research into the topic preceding the 1980s. The jump in the 1980s is described by some to be the second wave of AI (Holdsworth & Scapicchio, 2024), and can be described by meaningful but unspectacular breakthroughs such as NMLs. This excitement then plateaued until the mid-2010s, as few revolutionary developments were made. In 2015, however, publications went into overdrive. This surge in mentions can be explained by the proliferation of deep learning in 2015. Figure 3 shows the Google N-Gram results for "deep learning" between 2010 and 2022, which closely emulate the sweeping adoption shown in Figure 2.

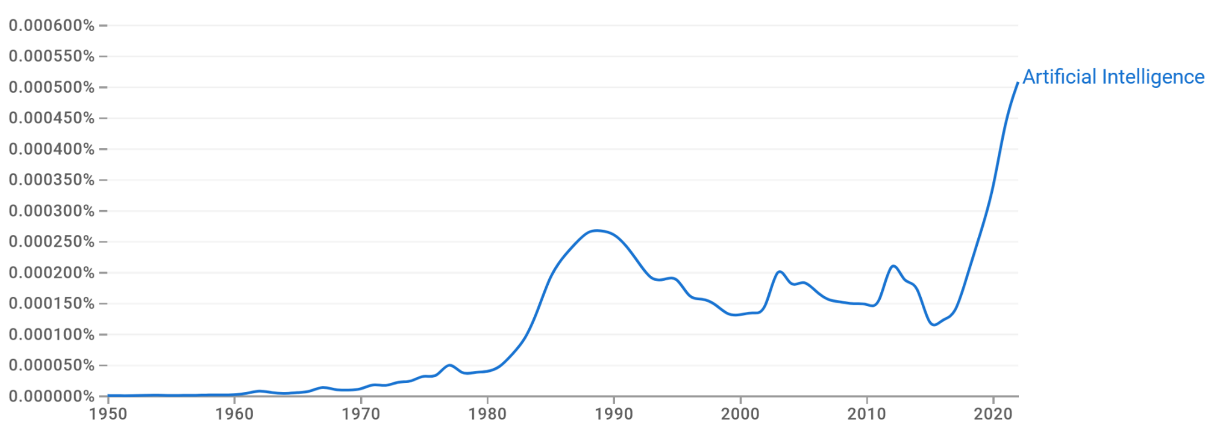

Figure 2. Google N-Grams results for "Artificial Intelligence" between 1950 and 2022.

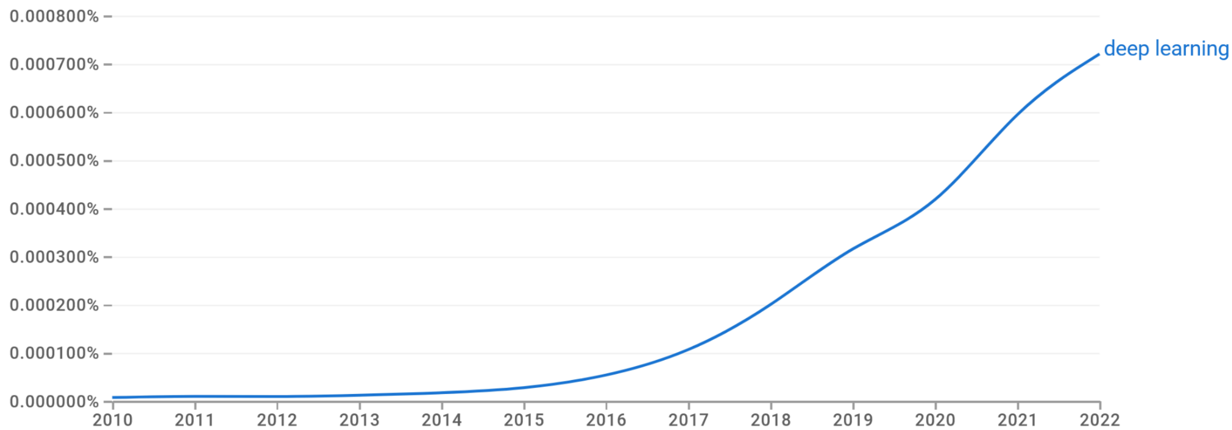

Figure 3. Google N-Grams results for “deep learning” between 2010 and 2022.

These publishing trends reveal an unprecedented surge in discourse around artificial intelligence between 2015 and 2022, signaling the development of a peak of inflated expectations following the success of deep learning models. This phenomenon is further supported by trends in private investment. Figure 3 presents data from Quid (2025) and the U.S. Bureau of Labor Statistics (2025), collated by Our World in Data (2025). It shows private investment in artificial intelligence increasing more than eightfold between 2015 and 2024, rising from $15.26 billion to $130.26 billion, with a peak of $145.4 billion in 2021. These figures show that artificial intelligence has garnered significant economic hype, an underlying mechanism of the hype cycle (Fenn & Linden, 2003). Goldman Sachs (2024)[1] shows concern regarding the full-bodied endorsement of AI seen across companies, and broadcasts fears that investments in the technology have outpaced reasonable expectations regarding what AI can deliver.

[1] This paper has since been retracted without cause. Due to a lack of evidenced claims regarding error in the report, one may speculate that its retraction was a business decision due to conflicting investments and market pressure.

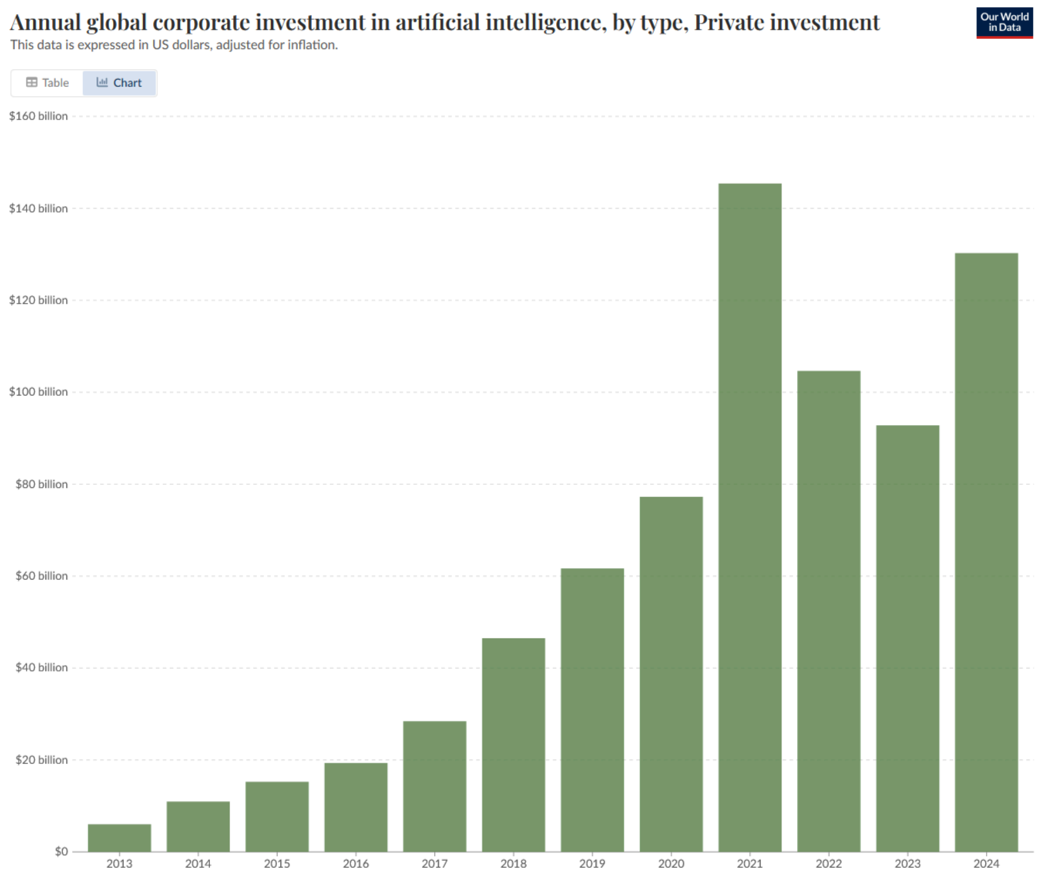

Figure 4. Global private investment in artificial intelligence by year between 2013 and 2024.

While undue excitement may seem harmless, it often comes at the cost of limited resources that require careful management. Artificial intelligence is run through data centers, massive warehouses of cooling towers and computational chips. These data centers are massive consumers of both clean water and electricity. It is forecasted that in 2027, AI will demand between 4.2 and 6.6 billion cubic meters of water, between 4 and 6 times the amount consumed by Denmark (Li et al., 2025). Data centers in 2020 consumed 64 terawatt-hours (TWh) in a year (EIA, 2021) and accounted for between 2.5 and 3.7% of the world's greenhouse gas emissions (Kilgore, 2024). This is indicative of the nature of waste within the industry. An interview with Dr. Deming Chen, AMD Center of Excellence director and IBM-Illinois Discovery Accelerator Institute co-director, explores how China's DeepSeek R1 AI was able to develop a product comparable to ChatGPT with lower cost, fewer chips, and reduced resource consumption (Laws, 2025). DeepSeek's success while using greatly reduced energy and training time showcases the often irresponsible development cycle that AI has followed by focusing much more effort on upscaling than improving efficiency. Such massive investments of not only capital, but finite resources, into speculative technology act as laissez-faire politics that put the climate further at risk.

Despite its faults, artificial intelligence has yielded several valuable breakthroughs. Beyond the hidden work AI has done for decades, managing data, aiding research, and making everyday items more convenient (Shao et al., 2022), contemporary AI has shown great promise in a handful of disciplines. Its use in wildfire predicting unmanned drones is enabling fast progress in wildfire management (Boroujeni, 2024), its implementation in biology is having vast effects in both understanding and treating cancer (NIH, 2024), and its predictive capabilities are being used to prevent energy losing instabilities in nuclear fusion (Poore, 2024). While artificial intelligence faces many hurdles and has stumbled over many already, absolute pessimism proposes its own drawbacks. Brian Merchant (2023), in *Blood in the Machine*, explores the Luddite movement in England, in which workers resisted technological change to protect their livelihoods during the Industrial Revolution. In analyzing the movement's ultimate failure, Merchant suggests that the shortcomings of technology could have been remedied through socially conscious regulation that benefited those it endangered. With public opinion polls of artificial intelligence falling (Faverio, 2023), the trough of disillusionment appears to be on the horizon, forecasting not only less investment into AI's detriments, but its potential benefits as well. Employing AI to solve genuine problems, when appropriate, is one way to progress its ethical and responsible development.

Sarewitz and Nelson's Three Rules for Technological Fixes predict the success of contemporary artificial intelligence differently, based on which grounds it is judged. Viewing AI as a system to manage and manipulate data yields wildly different results than judging it as an all-in-one solution to poorly defined societal woes, as current hype cycles seem to push (European Parliament, 2023). For this reason, it will be valuable to asses AI in both its forms, starting with AI as data management. Stryker and Kavlakoglu (2024) of IBM define rather reasonable goals of AI to be "automation of repetitive tasks," "more and faster insight from data," and "enhanced decision-making". Under this definition, the 'problem' here is a desire for stronger computing systems, more capable of manipulating data. Sarewitz and Nelson's first rule states that a solution must embody the cause-and-effect relationship connecting problem to solution. Roser (2022) demonstrates that AI has improved in reading, image comprehension, and predictive reasoning in recent years, revealing increasing data management abilities that solve the stated problem. Next, the effects of the technological fix must be assessable using relatively unambiguous or uncontroversial criteria. On this count, artificial intelligence for data management fails, not only because its success is hard to measure and comprehend (Coyle, 2025), but also because of the vast resources it currently consumes to operate. Furthermore, a decline in public opinion due to both consumed resources and anxieties over future developments demonstrates just some of the controversies relevant in its discussion (Faverio, 2023). Finally, the third rule states that AI must be built upon an established core. History dating back to the advent of computers supports this claim; since being formally named in 1956, artificial intelligence has been continuously developed, largely under the radar, until recent years. By satisfying two of Sarewitz and Nelson's Three Rules, AI in data management appears largely successful. Though concerns of resource use remain important, this framing suggests that AI is likely to succeed in this domain, provided it is developed responsibly.

As a phenomenon of hype, artificial intelligence faces new challenges under Sarewitz and Nelson's framework. Claims have been made that AI will help solve climate change, cure cancer, and much, much more. Rose (2023) echoes these claims and platforms some of the more hype-affected expectations. Under these criteria, AI is no longer solving the root problem. Climate change, for example, is a problem caused by technology; simply creating new technology does not acknowledge the cause-and-effect relationship. Similarly, AI for politics and healthcare misses the core of the respective problems. For these reasons, AI as a product of hype fails the first rule. AI for hype fails the second rule similarly to AI for data; with few ways to measure success and vast expenditures of vital resources, AI continues to court controversy. Hype oriented artificial intelligence fares no better against the final rule—AI as we know it today can not solve decades-old problems on a pre-existing technical core. Contemporary AI's recent emergence means it has little history in most problems, and there is little evidence that, until recently, it would be expected to. Unlike its use in data management, AI, as defined by hype, fails to prove itself a valuable fix under all three of Sarewitz and Nelson's rules. This necessitates caution in what can be reasonably expected from artificial intelligence, given how it is currently discussed and what it hopes to accomplish. Contrasted by the largely pragmatic role artificial intelligence plays in data management, hype has deeply altered public discourse and the projected success of this technology.

V. Conclusion

Hype seems to have failed not only artificial intelligence but countless other technologies. Overhype of cryptography and virtual reality (VR) has seemingly shown similar cycles for Blockchains and the Metaverse (Weaver, 2022; Zitron, 2023). Such exaggerated hype cycles are easily spotted when looked for—all three of these technologies have faced public backlash and disillusionment (Faverio, 2023; Faverio et al., 2024; Petrosyan, 2022). Vinsel (2023) claims that hype cycles are largely motivated by a fear of missing out, sustaining themselves only until they come crashing down. At the same time, however, none of these technologies are inherently bad. AI's contributions to research, cryptography to security, and VR to training simulators have all had positive impacts. The worry is allowing them to self-perpetuate past reasonable expectations of outcome at the cost of endangered resources. Economic analysis of AI reveals overinvestment as a result of hype, driving already high opportunity costs while environmental erosion ensues.

In the face of complex challenges, it is often easy to place faith in big, "Hail Mary" solutions, such as omnipotent computers capable of solving our problems. By abandoning pragmatism and neglecting proven, if difficult, solutions, we risk exacerbating the very problems we hope to fix. Given the risks of climate change, steps must be taken to ensure the ethical and effective development of solutions. This entails examining the expectations surrounding new technological developments and remaining vigilant against hype, and working to prevent reckless resource use when the returns are ambiguous. By effectively managing hype, we can ensure ethical and holistic development of solutions that are reasonably aligned with their outcome, allowing for the selection of solutions that effectively address the problem they aim to resolve.

VI. Resources

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