

**AIC-101 Introduction to Artificial Intelligence**  
**Assessment Activity AIC-101:00010**  
**Applying Knowledge of AI Systems and Concepts**

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“Artificial Intelligence”, “Machine Learning”, and “Deep Learning”. These three words have left a huge impact on the overall tech industry as well as the global economy since the introduction of OpenAI’s “ChatGPT” in November 2022<sup>1</sup>. This phenomenon shows the increase of product developments by tech companies<sup>2</sup> along with the mentions of “A.I.” by various news outlets and mainstream tech companies’ product events and earning calls, e.g. Google’s 2023 I/O event in California where the acronym “A.I.” was mentioned roughly 143 times during the two-hour presentation which approximately equates to the acronym being mentioned 1.153 times per minute<sup>3</sup>, Meta’s Q1 2023 earnings calls mentioned “A.I.” 56 times and Microsoft with 53 times<sup>2</sup>. These trends seem to suggest that “Artificial Intelligence” is going to be the latest and greatest technology that will completely change the world as we know it, it also seems to suggest that there is a re-emerging pattern of the “A.I. Boom” which was observed during the early 1980s where “expert systems” were being actively promoted, funded, and developed<sup>4</sup> but eventually ended with a two-to-three decade long “A.I. Winter”<sup>5</sup>. This raises a crucial question in the tech and business industry: Will the A.I. hype of the 2020s fade away similarly to the late 1980s?

To be able to answer the question above, we must first reflect on the history of the “A.I. Boom” and the “A.I. Winter”. Thomas Haigh’s opinion article titled “How the AI Boom Went Bust”<sup>6</sup> discusses the history of A.I. development from the 1960s to the 1990s where he begins by discussing the role of A.I. in education, covering how the subject has evolved parallel to the development of A.I. technology. Haigh highlights the subject’s shift from a marginal subject that was only recommended for master degree students and a small group of undergraduates during the late 1960s to a mainstream subject that can be considered as one of the “core subjects” in various computer science curricula. Haigh uses the presence of A.I. in academia to describe the atmosphere of the field during the 1970s where most, if not all, A.I. developments are focused on knowledge-based systems with the goal of understanding human language, also known as "symbolic language models".

Haigh proceeds to cover the rise of symbolic language models, specifically "expert systems", and the decline of said technology, mentioning the shift in the development of powerful reasoning machines to systems that are able to represent knowledge. During this period, the consensus on the goal of symbolic language models is to create a "general purpose reasoning engines driven by collections of individual facts", essentially a system that involves embedding logical schemas or elements and creating explicit set of rules which enables the program to manipulate these schemas. An example of such program is "SHRDLU" developed by Terry Winograd in 1971. Haigh delves into covering the abilities of the program that Winograd claimed, saying that it is able to understand natural human language, process commands via teletype and executing those commands in its block simulation. However, as impressive as it sounds, Haigh points out the limitations that these types of programs have: "...highly specialized systems, few of which were ever applied beyond carefully chosen problems.", essentially, such systems need highly specific instructions to be able to create the impressive response that Winograd claimed SHRDLU is able to produce.

Parallel to the creation of SHRDLU, comes a more advanced set of programs called "expert systems". The development of expert systems started in the 1960s by Edward A. Feigenbaum where he stated his focus for said systems is "to automate the work of human experts". The introduction of various expert systems resulted in a huge increase in private, public investments and startups. However, several issues start to become apparent as the development continued. DARPA concluded that several of its autonomous systems failed to reach its expectations, which, combining with budget cuts from the Reagan administration, inevitably ended with DARPA

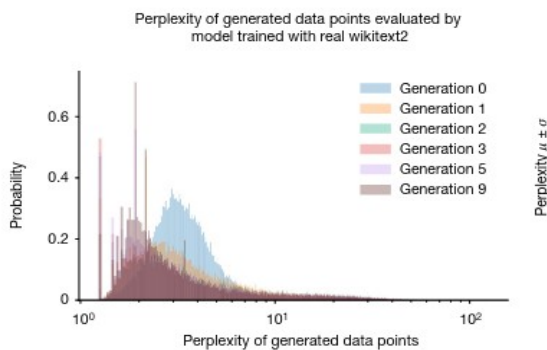
abandoning its work on autonomous systems, leading companies and startups to lose interest in further developments of expert systems as they are shown to be expensive to maintain as they require specialized developers to maintain such systems.

I very much agree with the author’s overall point as he manages to encapsulate how such technology can be carefully engineered to produce overblown outcomes, leading to a surge in popularity (hype), consequently resulting in huge investments and inevitably ending with a huge disappointment when the technology is unable to reach expectations. We can see a similar pattern emerging in the current A.I. atmosphere, however, before we are able to assess the current hype of A.I., we must take note on the current hype that is often associated with “A.I.” mostly surrounds its sub-category called “Generative A.I.”. These models are statistical models that identify different structures and patterns in their base training data which enables its ability to produce new text, images, videos and other forms of content<sup>7</sup>; these models are often used in contexts where users enter specific “prompts” or instructions and the model produces data from it<sup>8</sup>, a notable example of such models is Large Languages Models where they are able to generate text from users’ input; prime examples are such as OpenAI’s “Generative Pre-trained Transformer 4”<sup>9</sup> or “GPT-4”<sup>10</sup> that currently powers its chatbot, ChatGPT and Microsoft’s Bing AI.

The hype of these models both have similar characteristics to the “A.I. Boom” of the 1960s. First, they both have the notion of a “new” technology that produces seemingly amazing results e.g. ChatGPT’s ability to generate coherent paragraphs and texts<sup>11</sup>. Second, they both have wide range of press coverage and publicity whether it is on news networks, articles or magazines. And third, they both receive huge private investments from various tech companies along with spawning a wide range of new A.I. startups<sup>12</sup>. These three traits encapsulates the similarities between the hype of the 1980s and the hype of the 2020s which might suggest that Generative A.I. may be following the same trajectory as expert systems in the 1980s.

I believe that, over the next five years, the *hype* of Generative A.I. follow a similar downward trend as expert systems as issues surrounding the technology has become more apparent in recent times. Shumailov et al.<sup>13</sup> discusses the issue on the increase in unreliability of large language models as the human-generated data that is being used to train these large language models are gradually being replaced by LLM generated content which contributes to next-generation large language models becoming less accurate. The paper refers to such issue as the “model collapse”, consisting of two phases: the early model collapse and the late model collapse. The early model collapse shows the model beginning to lose information from the original data eventually leading to the late model collapse where the model generates results that have little resemblance to the original data.

Figure 1 shows a histogram of the perplexities of data produced by different large language models which are



evaluated by the very first model trained with the original wikitext2 data. The graph shows that over the generations, the models do tend to produce the same data as the original model with real data, however, the graph also shows the increase of tails in later generations which describes the models producing new data that the original model would have never produced. This demonstrates the risk of future generations of generative A.I. models producing less accurate information leading to user complaints and distrust.


Figure 1: Perplexity of generated data points evaluated by model trained with real wikitext2.<sup>13</sup>

Other researchers also delved into the effects that generative A.I. has on society. Bender et al.<sup>11</sup> presents the underlying issue of biases in LLMs in which they discuss the source material that being used to train mainstream LLMs which is retrieved through the method known as “web crawling”<sup>14</sup>. The paper shows that the data source for this training data set was crawled from user-generated sites such as Reddit where 67% of its users in the United States are men and 64% of its users are between the age of 18 and 29, and Wikipedia where only 8.8 – 15% of its users are women or girls<sup>15</sup> which, when combined with the unequal distribution of internet access across the planet, results in views by younger users and users from developed countries to be overrepresented in the dataset. The paper also mentions that the data crawled from user-generated sites can contain content that has themes of homophobia, transphobia and harassment towards groups such as people of color, queer people, immigrants, and other marginalized groups which can lead to LLMs amplifying biases and harms resulting in responses that exhibits racial biases, cultural stereotypes or negative sentiment towards specific groups of people<sup>11,16</sup>.

Lastly, figures and researchers have shown that the training of large language models and other types of A.I. has contributed major effects to the environment. In its 2024 environmental report, Google revealed that its carbon emissions have increased by 48% compared to 2019, a 13% year by year in 2023, which the company credited the increase of emissions to the “rapid advancements in and demand for artificial intelligence”<sup>17</sup>. Similarly, Microsoft, the company that OpenAI relies on to operate their GPT models, also revealed in its 2024 sustainability report where its carbon emissions increased by nearly 30% due to the company’s data center expansion<sup>18</sup>. In addition to these reports, independent researchers have also revealed more statistics of environmental impacts by LLMs. Li et al. revealed that Microsoft used approximately 700,000 liters of freshwater (from its electrical production process) during GPT-3’s training in its data centers<sup>19</sup> which according to the environmental news website, Earth.org, is equivalent to the amount of water used to produce 370 BMW cars or 320 Tesla vehicles<sup>20</sup>. These figures reflect the major effects that these LLMs have on the environment and as LLMs continue to become larger, largely due to the A.I. hype, more electricity from sources such as oil, coal and gas will be needed to power these huge data centers thus resulting in more carbon being emitted into the atmosphere inevitably speeding up the already concerning process of global warming.

In conclusion, I believe that, in the next five years, the “A.I. Hype” surrounding large language models such as ChatGPT, Gemini and other mainstream models will eventually grind to a halt due to its performance decline, ethical concerns, biases, and environmental effects that became more apparent in recent years. On the other hand, I do believe that the *technology* of language models will continue to be developed over the next five years by open source developers, hobbyists and tech companies<sup>21</sup>; popular open-source frameworks such as Ollama<sup>22</sup>, a community-driven project that enables any individual to run various large languages models e.g. Meta’s LLaMa illustrates that large language models are very popular among developers and are here to stay, and I concur that it is best for developers to continue its development with other machine learning technologies such as text-to-speech, speech-to-text or OCR to maximize the benefits of A.I. while also taking precautions in the ethical and environmental issues surrounding them; thus creating a more open, ethical and environmentally friendly technology for the human race and the planet.

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