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Review

A Primer on Generative Artificial Intelligence

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Abstract: Many educators and professionals in different industries may need to become more familiar with the basic concepts of artificial intelligence (AI) and generative artificial intelligence (Gen-AI). Therefore, this paper aims to introduce some of the basic concepts of AI and Gen-AI. The approach of this explanatory paper is first to introduce some of the underlying concepts, such as artificial intelligence, machine learning, deep learning, artificial neural networks, and large language models (LLMs), that would allow the reader to better understand generative AI. The paper also discusses some of the applications and implications of generative AI on businesses and education, followed by the current challenges associated with generative AI.

Keywords: artificial intelligence; AI; generative artificial intelligence; generative AI; GAI; GenAI; Gen-AI; ChatGPT; LLM; GPT; AI businesses; AI education; AI ethics; AI security

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1. Introduction

As the world experiences the Fourth Industrial Revolution, also known as Industry 4.0, it becomes essential to understand the various technologies relevant to Industry 4.0. These technologies include, but are not limited to, artificial intelligence (AI), blockchains, digital twins, and edge computing. AI has gained much momentum in recent years, and the release of ChatGPT in late 2022 has added to this momentum. Generative AI may play a role in environments such as manufacturing by providing information support and enhancing robotics [1]. Many educators may need to become more familiar with some basic concepts and technologies associated with AI and generative AI. Therefore, this paper serves as a primer on generative AI.

Simply put, generative AI generates content, which could be text, images, or multimedia. However, one must understand some of the basic concepts before taking a deeper dive into generative AI. Hence, this paper starts with an explanation of AI and the relevant AI tools and techniques, followed by an introduction to generative AI (Gen-AI). Additionally, this paper briefly touches upon some of the applications of Gen-AI, followed by challenges and opportunities associated with Gen-AI and future recommendations.

2. Artificial Intelligence

We will start our discussion with the meaning of intelligence. There are several definitions and attributes of intelligence. Britannica defines intelligence as the "mental quality that consists of the abilities to learn from experience, adapt to new situations, understand and handle abstract concepts, and use knowledge to manipulate one's environment" [2]. While this may not be the absolute agreed-upon definition of intelligence, the definition mentions some critical concepts associated with intelligence. Many of the concepts associated with intelligence also apply to AI; therefore, as we take a deeper dive into AI, we should reflect upon the relevance of this definition to AI.

Artificial intelligence (AI) has gained much momentum in recent years due to the advancements in hardware and software technologies. AI has several definitions, and some of them share similar attributes. Some of these definitions are listed as under:

- It "is the study of how to make computers do things which, at the moment, people do better" ([3], p. 3).
- "Artificial Intelligence (AI) is a way to make machines think and behave intelligently." ([4], p. 8).
- "Artificial Intelligence is used to describe computer systems that demonstrate human-like intelligence and cognitive abilities, such as deduction, pattern recognition, and the interpretation of complex data" ([5], p. 386).
- [AI] "is the ability of a computer system to perform task that normally require human intelligence" ([6], p. 287).

These definitions allude to making machines behave with "intelligence" as humans do. AI can be classified into three distinct categories: artificial narrow intelligence (ANI), artificial general intelligence (AGI), and artificial super intelligence (ASI).

2.1. Artificial Narrow Intelligence

Artificial narrow intelligence (ANI), also known as weak AI, is a form of AI that is limited in functionality to limited tasks. Some examples of ANI include email spam filters, movie recommendation systems, and online shopping website recommendation systems. ANI is generally more efficient than humans in performing a specific or limited number of tasks. For example, it can identify patterns in large datasets more efficiently. ANI is the only type of AI that exists today [7].

2.2. Artificial General Intelligence

Artificial general intelligence (AGI), or Strong AI, is the next level up from ANI. AGI is focused on performing tasks at the same capacity level as humans. If a machine achieves AGI, it can understand the world similarly to humans [8]. AGI aims to create machines that can constantly learn and improve their abilities and are indistinguishable from human beings [9]. The realization of AGI is many years away because it aims to tackle the concept of machines that possess generalization abilities [10].

2.3. Artificial Super Intelligence

Artificial super intelligence (ASI) is different from artificial general intelligence. ASI is "significantly more intelligent than humans in all respects" ([11], p. 397). Such machines may have their own needs, beliefs, and desires [7]. Currently, ASI is theoretical.

2.4. Artificial Intelligence and Human Intelligence

The Turing test, proposed by Alan Turing [12], deals with the question of whether machines can think. To elaborate on this, let us consider a scenario with three participants: a human (H), a machine (M), and a human interrogator (H-I). Let us assume that the machine and the human are hidden from the H-I. Now, the H-I asks the machine and the human a series of questions. The H-I cannot see who is responding to the question, but the H-I can only see the response. If the H-I is not able to differentiate between the human response and the machine's response, then in such an instance, the machine has passed the Turing test.

Earlier in this section, we discussed the definition of intelligence. Some of the critical attributes of intelligence were (a) the ability to learn from experience, (b) adapting to new situations, (c) understanding and handling abstract concepts, and (d) using knowledge to manipulate one's environment [2]. In light of the definition of intelligence, it is evident that ANI, which is focused on a specific task, continuously improves by learning from experience and applying the knowledge to new situations. The ultimate goal would be to have machines that possess the intelligence of humans, so they are indistinguishable from humans, thus passing the Turing test. However, while AI has advantages over human intelligence, such as increased speed, the ability to communicate with many different systems effectively, and the ability to reconfigure itself, human intelligence can efficiently achieve complex goals through things such as motivation, emotion, creativity, and mutual understanding [13].

With a basic understanding of AI, the following sections provide an overview of how machines acquire intelligence. We will start our discussion with symbolic artificial intelligence, which was a dominant technique until the 1980s. Then, we will go into statistical-based techniques such as machine learning and deep learning.

3. Symbolic Artificial Intelligence

Before going further into statistics-based algorithms, it is essential to acknowledge and briefly discuss the role of symbolic AI. Symbolic AI was a dominant approach until the late 1980s [14]. Symbolic AI differs from the current data-driven AI techniques that utilize statistical algorithms. Symbolic AI (SAI) utilizes various symbols representing different objects and their relationship; for example, the objects could be fruits, vehicles, and humans. Some examples of the relationships between humans and vehicles could be "humans own vehicles," "humans drive vehicles," and "humans sit in vehicles." Such relationships are defined using formal language that computers can manipulate [15].

An expert system is one of the most famous examples of a symbolic AI. An expert system is "an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution" [16]. Expert systems use rules to provide recommendations. Expert systems are used in different fields; a prime example is medicine. For example, an expert system can support a doctor selecting and prescribing medication based on the following rules:

If the patient has a cough, then provide medicine A.
If the patient has a cough and a fever, then provide medicine B.
If the patient has a cough, a fever, and a sore throat, then provide medicine C.

Symbolic AI has some strengths and weaknesses. Transparency is one of the main strengths of SAI because it is easy to interpret how a conclusion is drawn [17]. Some of the limitations of SAI include (a) a lack of scalability because it requires complete and proper knowledge to function, and (b) it cannot learn and refine by itself [17]. The limitations posed by SAI can be addressed by machine learning and deep learning algorithms, discussed next.

4. Machine Learning

For computers and machines to act intelligently, they need to learn, hence the term machine learning. Machine learning is a subset of AI. Like AI, there are different definitions of machine learning (ML), as under:

- Machine learning "allows the computer to learn automatically without human intervention or assistance" ([5], p. 386).
- "Machine Learning is about making computers modify or adapt their actions (whether the task is making predictions or controlling a robot) so that these actions get more accurate with experience, where accuracy is measured by how well the chosen actions reflect the correct ones." ([18], p. 5)
- "Machine learning is considered an extension of predictive analytics. It occurs when systems of algorithms automatically improve themselves based on data patterns, experiences, and observations" ([6], p. 287).

So, machine learning is about algorithms and techniques that allow machines to learn from data. Two main categories of machine learning techniques are supervised machine learning (SML) and unsupervised machine learning (USML).

4.1. Supervised Machine Learning

As the name implies, a supervisor (or teacher or trainer) exists in supervised machine learning. The supervisor's role is to train the machine in using labeled data. For example, the machine may be provided with many examples of automobile images that will subsequently be labeled as automobiles. The machine learns from this data, and then the machine is provided with a new data set. The goal of the machine is to identify automobiles in different images accurately. This identification of new images is based on various statistical methods, such as regression. Hence, in supervised learning, the outcome variable or target variable is known [5]. There are two main categories of algorithms in supervised machine learning: classification and regression. Classification contains a set of algorithms used to identify a label or category for a given input and is used when the target variable is categorical. Regression is a set of techniques that are used for predicting an outcome or a relationship between one or more independent and dependent variables. Regression is generally used when the target variable is continuous.

4.2. Unsupervised Machine Learning

As the name implies, in unsupervised learning, there is no supervisor (or teacher or trainer). The machine is responsible for analyzing the data and finding patterns in the data, and based on those patterns, it will put the data in different categories. For example, a machine is provided with thousands of images of apples, bananas, and oranges. The machine will then look for patterns, such as shape, texture, and color, to group them into similar categories. So, a machine may see something round with a groovy surface and an orange color and group that into one category. Hence, unsupervised learning is used for exploration, dimension reduction, or pattern recognition [5]. Dimension reduction becomes important in large datasets with many variables, also known as features or dimensions. A detailed discussion of dimension reduction is beyond the scope of this paper; however, simply put, the goal of dimension reduction is to reduce some of the features or variables from a dataset without losing any critical information.

There are two main categories of algorithms in unsupervised machine learning: clustering and association. Clustering contains a set of algorithms used to group unlabeled data into different categories based on similarities or differences. Association is a rule-based algorithm used to find the associations between different data in a dataset. They are often helpful for marketing because they help identify associations between different data points; for example, a person is likely to buy a toothbrush if the customer has also purchased a toothpaste.

5. Deep Learning

This section will briefly describe deep learning, a subset of machine learning (Figure 1). Deep learning differs from machine learning in many aspects; for example, machine learning generally uses structured data but can also use unstructured data. However, the unstructured data must be pre-processed to convert it into a structured format for machine learning algorithms [9]. On the other hand, deep learning utilizes unstructured data without pre-processing. Some additional key differences between deep learning and machine learning are discussed in Table 1 [19,20].

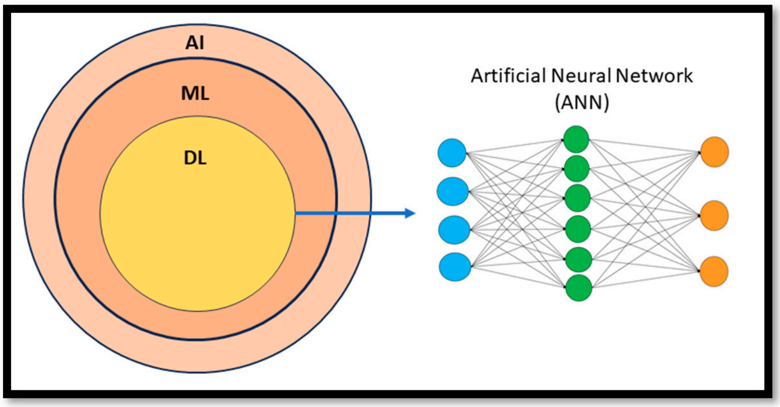

Figure 1. Relationship between AI, machine learning, deep learning, and ANN.

Table 1. Differences between machine learning and deep learning.

Machine Learning	Deep Learning
Requires a relatively small amount of data for training and prediction.	Requires large amounts of data for training and prediction.
It does not require extensive computational power, and low-end central processing units (CPUs) may be sufficient.	High-end computational power is required. A graphic processing unit (GPU) is needed.
The time to train the model is relatively small.	The time to train a model is relatively high.
Simple linear correlational models.	Non-linear complex correlational models.
The output of machine learning algorithms is generally a numerical value.	The output is not limited to a single numeric value but could be in different formats.

Deep learning is inspired by the human brain and utilizes artificial neural networks (ANN). In order to understand deep learning, it is crucial to understand artificial neural networks (ANN), which are introduced in the next section.

Artificial Neural Networks

Artificial neural networks (ANN) "Mimic the neural structure of the brain using learning, memory, and generalization. As a result, neural networks can capture highly complex relationships in the data and are used as a building block of sophisticated machine learning system (often called deep learning)" ([5], p. 435). In simple terms, an ANN comprises multiple layers, as shown in Figure 2. The first layer is the input layer, and the last is the output layer. Several hidden layers are between the input and output layers. Each hidden layer takes input from the previous layer, performs some calculations, and passes the output to the next layer based on the calculations. The next layer will perform similar calculations and pass the output to the next layer in line. This process continues until the output is fed to the output layer, which provides the final result or prediction.

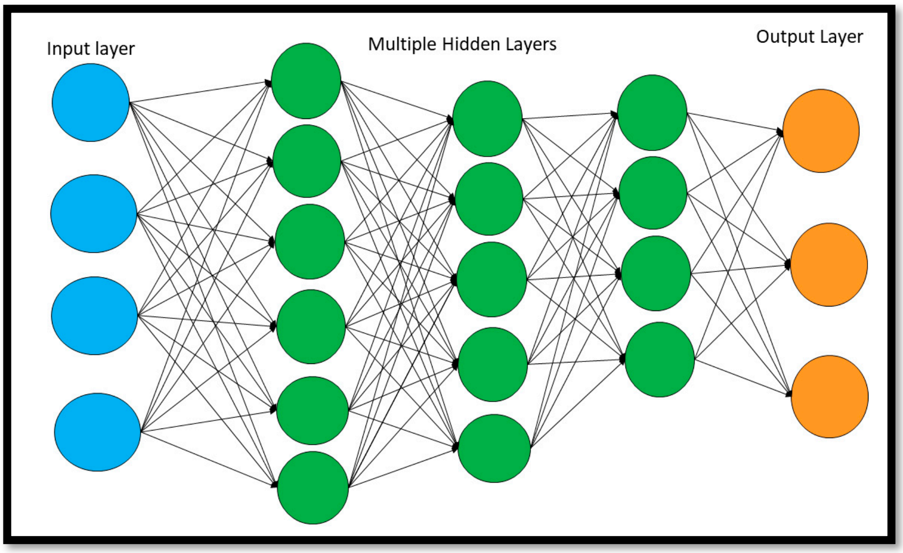

Figure 2. Artificial Neural Network.

Let us discuss the above with some technical details using an example. Let us say an image of the alphabet "A" is fed to an ANN for identification (Figure 3).

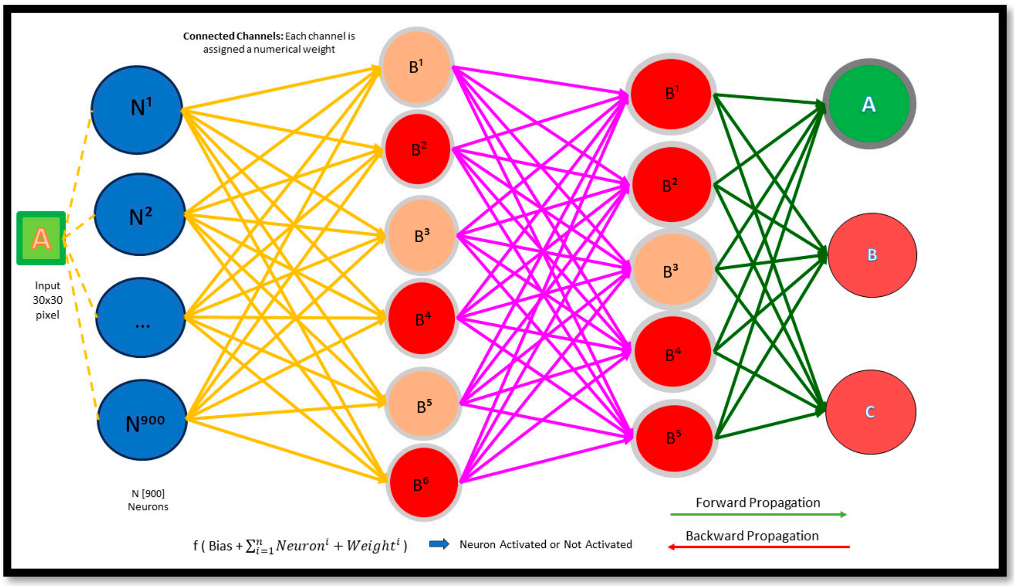

Figure 3. Identifying an image using ANN.

1. Let us say that this picture is 30 × 30 pixels. Hence, there are 900 pixels altogether.
2. The 900 pixels are fed to 900 neurons in the input layer of the ANN.
3. Each neuron has a number associated with it, which is known as "bias". The bias is akin to an "intercept" in a simple linear equation that has the form of Y = mX + b. The bias provides a level of flexibility.
4. The information is transferred from one layer to another layer through "connected channels." Each of the channels also has a "weight" associated with it. The weight identifies the strength of the connected channel between two neurons.
5. Before going to the next step, let us consider a simple example that may help us understand the relationship between "weight" and "bias" using a non-neural network example:
    a. A teacher typically provides students with an assessment strategy to identify how the assessments are weighted to calculate the final course grade. For example, the final exam may be worth 30% of the final grade, the final project may be worth 20%, and there may be five quizzes, each worth 10% of the final grade. These percentages are considered the "weights"; the higher the percentage, the more influence it will have on the final grade
    b. Continuing with the same analogy, in some instances, the teachers may use their discretion to make some adjustments to the final grade, e.g., sometimes they may curve an assessment or adjust the score of a specific student based on some knowledge about the student. An example could be that a student may have performed exceptionally well on different assessments throughout the semester. However, due to an unavoidable family emergency, the student may not have performed well on a given assessment. Therefore, the teacher may make some discretionary adjustments for this student. The discretionary adjustment or the curving of grades may fall under the category of bias. Using the example of the simple linear equation (Y = mX + b), "m" would represent the different "weights" for the assessments, "X" would represent the "score" of the given assessment, and "b" would represent the "bias".
6. Now, going back to the discussion of ANN, the bias is added to the weighted sum of inputs that reach the neuron, which is then applied to a function known as the activation function. Using the earlier analogy of an assessment strategy for a final grade calculation, the bias is only added after all the different assessments are added based on their weights.

7. Simply put, an activation function produces an output based on an input. The role of the activation function is to determine if a neuron should be activated. If the neuron is activated, it passes the datum to the next neuron.
8. If the input for a given neuron exceeds a certain threshold, the activation function will activate it, and the datum is passed on to the next layer; otherwise, nothing happens to the neuron. The activated neurons pass the datum to the next layer, and the same process is repeated until it reaches the penultimate layer before the output layer.
9. The last hidden layer activates the neuron corresponding to the image of the alphabet letter "A." It activates the neuron in the output layer that identifies the image of the alphabet letter "A."
10. Once a prediction has been made and the datum is misidentified, adjustments must be made in the ANN. This adjustment is known as backward propagation. As part of the backward propagation, the weights and biases are updated. The entire process is iterative, and the artificial neural network is constantly updated.

6. Generative Artificial Intelligence

With a basic understanding of artificial intelligence, machine learning, and deep learning, let us turn our attention to the main objective of this paper: generative artificial intelligence (Gen-AI). In the most simplistic terms, the word "generative" implies "generate," "produce," or "create." Therefore, generative AI is capable of generating content. "Generative artificial intelligence (AI) describes algorithms (such as ChatGPT) that can be used to create new content, including audio, code, images, text, simulations, and videos" [21]. Although generative AI has been around for a few years, the release of ChatGPT in late 2022 has put Gen-AI under the spotlight. In order to get a better understanding of Gen-AI technology like ChatGPT, it is essential to understand a few additional concepts such as natural language processing (NLP), large language models (LLMs), and a generative pre-trained transformer (GPT).

6.1. Natural Language Processing

Natural language processing (NLP) focuses on designing and using computer programs to analyze or generate human language [22]. "The goal of Natural Language Processing (NLP) is to analyze, understand, and generate languages that humans use naturally so that eventually a computer will 'naturally' be able to interpret what the other person is saying" ([18], p. 10). There are three reasons for a computer to perform NLP: (1) to communicate with humans, (2) to learn, and (3) to advance scientific understanding [23].

6.2. Large Language Model (LLM)

A language model (LM) allows us to "predict what words are likely to come next in a text, and thereby suggest completion of an email or text message" ([23], p. 824). A language model uses probabilities to predict words that can occur in a sentence. For example, if the first word of a sentence is "they," then the probability of the second word being "are" is a lot higher than "is".

6.3. Transformer

A transformer, also known as a transformer model, is a type of artificial neural network. It transforms input from one format to another [24]. In simple terms, a transformer takes an input and produces an output that sometimes may be in a different format. For example, it can take input as a written prompt, and as an output, it may create a written essay or email or generate an image or audio.

6.4. Generative Pretrained Transformer (GPT) and ChatGPT

Generative pretrained transformers (GPTs) are a family of artificial neural network (ANN) models. These ANN models produce a sequence of words, code, or other data based on an input via the prompt [25]. There have been different iterations of GPTs, such as GPT1, GTP2, GPT3, and GPT4. There are various Gen-AI tools that utilize GPTs, the most famous one is ChatGPT.

So, what exactly is ChatGPT? In light of the earlier discussion, it is a form of generative AI that utilizes artificial neural networks (ANN) and large language models (LLMs) to create an output based on an input prompt. ChatGPT "is trained to follow an instruction in a prompt and provide a detailed response" [26]. In semi-technical terms, it is a Chatbot that utilizes AI, NLP, and LLM to communicate with its audience.

6.5. Generative AI Tools

Generative AI is a machine learning model that can generate new data instead of making predictions [27]. The new data can be audio, code, images, text, simulations, and video [21]. ChatGPT has gained popularity since it was released to the general public around November 2022. However, aside from ChatGPT, other generative AI tools are utilized for various other purposes. For example, some generative AI tools generate images based on text prompts. Such systems utilize language models trained with text and image data [28]. Some image-generation AI tools include Bing Image Creator, Craiyon, DALL-E2, DreamStudio by Stability AI, Dream by WOMBO, Midjourney, and Myheritage's AI Time Machine [29].

7. Application of Generative AI

Generative AI will have an impact on the society as a whole. This will include individuals, businesses, and organizations. While it is true that technology can replace humans, it can also support humans in different shapes and forms. Generative AI can provide opportunities to support employees and make the organization more productive [30]. While several organizations are developing generative AI solutions, the current major players are Amazon, Google, IBM, Microsoft, and OpenAI [31]. This section provides a glimpse of some of the applications of generative AI.

7.1. Business

Generative AI can augment human creativity by promoting divergent thinking, collaboration, idea refinement, idea evaluation, and challenging expertise bias [32]. For example, generative AI tools can generate multiple ideas quicker than humans, allowing humans to evaluate their viability. A study was conducted to compare human creativity to that of AI Chatbots using the Alternative Use Task (AUT), which assesses divergent thinking [33]. They found that while the AI chatbots generally produced more creative ideas, the best human ideas still matched or exceeded those ideas [33]. In another study, researchers compared the combinational creativity capability between humans and DALL.E and found that DALL.E performed very closely to novice designers [34]. Of course, this does not mean that generative AI ideas are superior to humans. However, it means that one additional tool is available for humans to generate and evaluate new ideas.

For businesses, generative AI can be utilized in many scenarios, such as customer experience and service, marketing, healthcare, entertainment, human resources, and more [31,35,36]. From a sales and marketing perspective, a company can use predictive modeling to predict when a customer will likely purchase a product [37]; then, generative AI can produce custom marketing messages for the given customer. According to Gartner, by 2025, 30% of marketing messages will be synthetically generated [31]. Generative AI tools can be utilized in the initial phases of innovation, such as ideation and digital prototyping, which leads to faster iterations and reductions in development costs [38]. In medical sciences, generative AI such as artificial neural networks are being investigated to develop antibodies [39]. According to Gartner's prediction, by 2025, generative AI techniques will be used to discover more than 30% of drugs [31].

7.2. Education

Artificial intelligence (AI) is not new to the domain of education. In education, AI has been around for over 40 years in different shapes and forms, such as intelligent tutoring systems [40]. AI can support school administration, teachers, and students in different capacities.

AI can provide a competitive advantage in higher education institutions in teaching and learning, recruitment and retention, and student advising [41,42]. AI can be used for student retention [43] by developing models that predict students at risk of failing or dropping out. One study explored some of the challenges associated with traditional student advising systems and proposed a framework for an AI-based academic advising system [44]. AI-based tools can provide customized recommendations to improve student success [45]. Likewise, chatbots can provide 24/7 academic support services such as library services [46] and improved student support services [47].

Generative AI tools like ChatGPT can also support educators. It can be used for developing material such as learning units and various assessments; however, it is equally important to use this tool responsibly to promote critical thinking [48]. ChatGPT can promote equity for students by leveling information access and creating effective learning strategies for diverse learning styles [49]. It has also been known to support the assessment of student work and to recommend improvements to teaching strategies [50]. However, one must understand that the current version of ChatGPT, as of this writing, needs to be improved in functionality and is likely to contain some factual errors. Unlike humans, such tools cannot create differentiated instructions for specific students [51].

Students can also benefit from AI or generative AI tools. In one study, medical students positively perceived the impact of AI in healthcare and medical education [52]. While the positive perception of AI in medical education is encouraging, broader studies are warranted to understand students' perceptions of AI in medical and other educational fields. Generative AI tools such as ChatGPT can have educational applications if utilized correctly. Generative AI can potentially revolutionize intelligent tutoring systems (ITS) by providing learners with a more personalized learning experience. Generative tools like ChatGPT can provide personalized learning experiences for students [53–55].

However, there are also concerns that students may misuse such tools; hence, universities are taking various steps to prevent misuse. Some institutions have banned such tools altogether, while others are reviewing and updating their policies [56]. Eight out of the 24 universities in the UK Russell Group consider using AI bots to be academic misconduct [57]. It is also recommended to update assessments by making them AI-resistant by incorporating multimedia or other content that AI may not be trained on [58]. Some universities are redesigning their assessment procedures by incorporating the traditional pen-and-paper method instead of having a computer-based exam [59].

8. Challenges of Generative AI

While generative AI provides many benefits, there are challenges and concerns as well. This section discusses some of these challenges and concerns.

8.1. Business Competition

Generative AI requires various resources, including, but not limited to computational resources, data, and talent. Having appropriate resources can pose challenges for relatively smaller organizations to enter this market and could be a cause of concern from a competitive perspective [60]. This can create an unfair advantage for some businesses and hurt consumers. Large firms can refuse to give access to their language models, refuse to grant access to their data, or create steep barriers for switching firms, therefore locking in smaller businesses that are forced to use their firm due to lack of resources [61]. An executive order passed by the United States president urges federal agencies to promote competition in AI by stopping unlawful collusion, preventing dominant firms from disadvantaging competitors, and providing new opportunities for small businesses and entrepreneurs [62].

8.2. Explainability of Artificial Intelligence

The explainability of AI is not a new problem [63], and it has become a more significant barrier in light of the advancements in machine learning in a short period [64]. Explainability is an expectation that makes the decision-making process of an AI model more transparent [65]. Understanding the intricacies of any model is unrealistic for people not in the field of developing mathematical models and algorithms. For example, a medical doctor cannot be expected to be an expert in probabilistic and statistical modeling. However, such professionals are likely to use the output of AI as part of their decision-making process. Therefore, should these individuals unquestioningly trust the output or recommendations of the AI systems? This becomes even more important for domain specialists in other fields, such as medicine and the military [66]. Hence, there is a need for explainable AI (XAI).

XAI is a set of processes and techniques that allow humans to understand and trust the output of machine learning algorithms [67]. Such techniques could be classified into categories such as (a) white box vs. black box techniques, (b) model-specific techniques vs. model-agnostic techniques, and (c) global vs. local interpretation [68]. XAI is a multidisciplinary area of research that consists of many different fields that often do not interact [69]; therefore, creating XAI requires the close collaboration of fields such as artificial intelligence, cognitive sciences, computer science, and human–computer interaction, to name a few.

8.3. Accuracy—Facts, References, and Results

Generative AI depends on data; such systems' output is only as good as the data fed into these systems. Therefore, it should be understood that information produced by generative AI can also be inaccurate; hence, it should be verified [31]. For example, in 2022, Meta unveiled a large language model (LLM) called Galactica that was trained on scientific literature and was intended to support the scientific community. Unfortunately, the LLM was shut down after three days because it produced incorrect results [70].

8.4. Ethics

Sometimes, there is a fine line between law and ethics, which can be blurry. While something may be ethical for one person, it may be unethical for another person. Likewise, using technology such as generative AI can cause ethical concerns. Let us discuss a couple of examples:

Have you ever wondered how machines are trained to identify data? In some cases, identifying images involves the use of humans. One must remember that it is not only about identifying nice images; the machine must also recognize graphic and gory images. OpenAI caused adverse side effects on workers from Kenya, who were paid less than 2.00 USD per hour, by requiring them to label graphic data to reduce the graphic content on ChatGPT [71]. These workers had to endure viewing graphic images. Unfortunately, people from third-world countries are often taken advantage of under the guise of serving humanity when they are actually serving influential organizations.

Academic concerns exist for students who use such tools as part of their projects and homework and take credit for the work without acknowledging the use of such tools. The concern for academia is the need for more tools to detect the usage of such tools [72]. Although there may be tools to detect plagiarism and AI-generated content, they are not always foolproof [73]. Some educators are reevaluating their assessment strategies and finding creative ways to incorporate such technologies, which is a step in the right direction [74]. For example, (a) rather than just simply asking students to write an essay, they may ask the students to watch a video and synthesize it; (b) rather than asking students to write code from scratch, students are provided partial code and they are required to update the code to meet specific requirements.

8.5. Legal Issues

Often, with any technology, legal issues must also be addressed. Likewise, there can also be potential legal issues with LLM due to internet data scraping [73]. There is already a copyright lawsuit against OpenAI [75], the most recent being filed by the New York Times against OpenAI and Microsoft for copyright infringements [76]. Due to a lack of proper regulations, entries into ChatGPT may become part of the public domain and could potentially expose an organization's intellectual property [31]. Samsung banned the use of ChatGPT after an accidental code leak [77], and other companies like Amazon, JP Morgan Chase, Verizon, and Walmart have also taken steps to minimize or ban the use of ChatGPT [78].

8.6. Security

Generative AI tools are also prone to cybersecurity issues. Seventy-nine percent of the IT leaders surveyed reported security concerns with these technologies [79]. Generative AI tools can defend or attack a system [80]. There are other security risks, including, but not limited to, the exploitation of personal or professional data entered into such systems [81]. A study found that a little less than forty percent of the job tasks in the Australian workforce have direct exposure to LLMs, putting workers at risk for cybersecurity risks such as unauthorized access, system manipulation, or data theft from malicious actors [82]. Bad actors may use AI jailbreaking techniques to attack organizations' AI models and assistants to reveal sensitive information [83].

8.7. Intellectual Growth

In the early 1990s, many people could quickly memorize several telephone numbers by heart. Fortunately, mobile phone technologies have allowed humans to offload this cognitive task to computers. Unfortunately, a negative side-effect is that people stopped exercising one of their mental skills. Technology has provided various opportunities for humans to offload various computational or cognitive tasks to computers. This may be good for routine and mundane tasks but not for higher-order thinking tasks. This can be a cause of concern for researchers because it may also impact their ability to articulate their thoughts [73]. Similarly, a study reported that students whose work seemed to have generative AI content could not think critically during their oral presentations [84]. There is a risk of overreliance on generative AI, specifically in students, that can cause failure in developing skills, such as problem-solving and critical thinking [49].

8.8. Sustainability

Generative AI requires significant electricity [31]. Some of these computationally intensive algorithms require significant energy, which can be a cause of concern from an ecological perspective [73]. For example, GPT3 required 1.287 gigawatt hours and 700,000 liters of clean freshwater to be trained; 1.287 gigawatt hours is the amount of energy required to power 120 U.S. homes for one year [79]. While generative AI requires significant energy, it also can reduce energy usage in the IT sector through initiatives such as Google's DeepMind AI, Microsoft's AI for Earth initiative, and IBM Watson AI, which can examine a data center's energy usage and forecast demand in order to modify power management and lower energy waste [85].

9. Discussion and Conclusions

AI and the associated AI tools are here to stay, and society must adapt. Businesses and academic institutions must invest in these tools to stay caught up. Businesses must invest in technologies and talent development to ensure they are competitive. Businesses must have talent to work alongside technology [86]. Generative AI should not be viewed as a tool to replace humans but rather as a tool to support humans [79].

The role of data governance within an organization has become even more critical. A clear and actionable framework must exist to utilize generative AI [79]. Organizations should have proper protocols to avoid exposing their intellectual property through the use of generative AI tools [31].

Academic institutions and accrediting bodies should reevaluate their curriculum. AI will impact every field, whether it is art and humanities, social science, medical science, or engineering, to name a few. The curriculum should have at least one course to educate the students on AI and the impact of AI in their respective fields. Additionally, guidelines related to cheating and plagiarism will have to be reevaluated.

Everyone is trying to cash in on generative AI. Entire applications may be developed using generative AI, which may not be entirely secure or tested. It is one thing to write and unit test a small standalone program. However, writing a standalone program differs significantly from an enterprise application that could interface with other systems. So, checks and balances must be in place; otherwise, it may be costly for businesses and consumers.

As stated earlier, generative AI is here to stay for the long run. Whether we like it or not, people will continue to use it. The bad actors in society will also continue to use it. So, various stakeholders, such as governments, businesses, and academic institutions, must collaborate to educate businesses and society on the healthy use of such tools and ensure the tools are not misused. We have just touched the tip of the iceberg. There is significant work that needs to be done on many fronts to address challenges and opportunities in various domains, including, but not limited to the arts, humanities, businesses, education, government, healthcare, law, engineering, ethics, privacy, security, hard sciences, social sciences, and sustainability, to name a few. Broader research is warranted in various domains to address technical and socio-economic challenges and opportunities.

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