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FACT SHEET

APRIL/MAY 2023
NUMBER 2023/02

2023

AI IN HR: EXAMPLE OF CHAT GPT

Introduction

Chat GPT and other examples of what is termed as generative artificial intelligence (AI) have gathered much media headlines and captured our collective imagination. We are excited and startled both by the type of responses we receive from these AI applications to our prompts and the exponential use and adoption of these applications. And we are intrigued as well as fearful about the possible capabilities of the AI application.

In this Fact Sheet we explore what generative AI is and we will focus in on Chat GPT as a specific example. We begin with the terms AI, machine learning, and deep learning that are mostly cited in popular discourse. We then describe generative AI. Thereafter, we centre our focus on Chat GPT as an example of a Large Language Model of generative AI and describe what this means. Following this we explore its possible uses in HR and some of the considerations regarding ethics, governance, risk, and compliance. We need to ask what abilities we are attributing to AI and, relatedly, what creation, judgment, and decision-making roles are we then allocating to AI. This leads to a discussion on definitional issues and the analogies drawn between humans and machines or AI as well as the attributions of human intelligence or cognition to machines or AI. We end the Fact Sheet with a discussion on a way forward. We return to the themes we identified to understand our evolving context in the **October 2022 Fact Sheet**, such as embracing the future, and provide a practical example of how we can embrace and implement AI.

For a quick reference for the differentiation between AI, algorithms, and automation see the **July 2020 Fact Sheet**.

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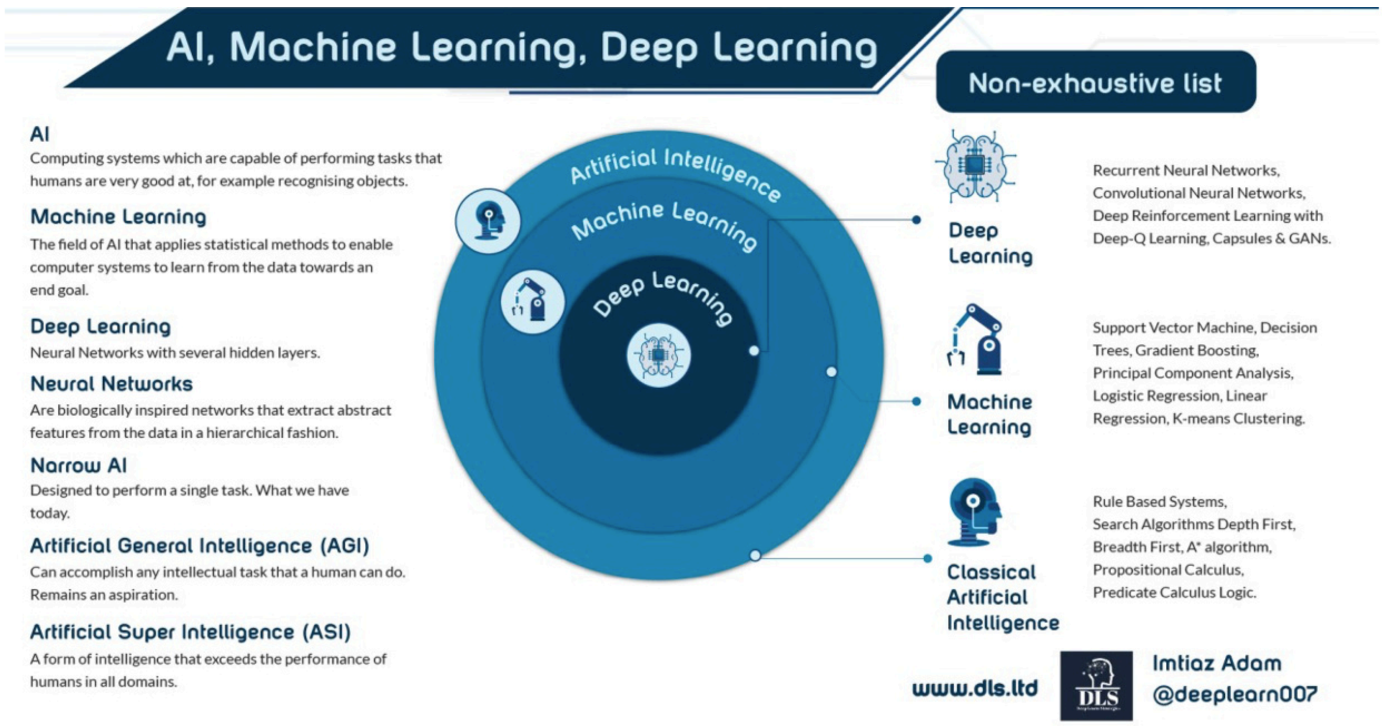
AI, machine learning, and deep learning

Generally, we find three main terms in the media in relation to computing or machine capabilities: AI, machine learning, and deep learning. At times these are used interchangeably. Machine learning (ML) though is one field of AI. A subset of machine learning is deep learning. It is based on what are termed artificial neural networks, which are derived from specific models of neurons and their activities (or neural networks) in the brain. Deep learning is a reference to the 'deep layers' (or number of processing layers) of these networks that help to process data. [1]

The relations between AI, ML and deep learning are illustrated in the diagram below. The diagram also has brief, practical descriptions of various terms, including the difference between narrow AI and broad AI or Artificial General Intelligence (AGI).



Source: I. Adam (2020) [2]

See the following video on AI, ML, and deep learning: **Click Here**

Deep learning methods are utilised by a category of machine learning applications termed as generative AI.

1. For an illustration of the multilayers, see the figures in the later section on definitional issues.
2. **https://www.linkedin.com/pulse/future-ai-part-v-cutting-edge-imtiaz-adam**

Generative AI

We can describe generative AI as a class of machine learning models comprising of neural networks and algorithms (or set of computing instructions or procedures to solve problems and complete tasks). It is claimed that this specific type of AI[3] has the capability to generate new content or output and hence the name generative AI. It can "*generate new outputs* based on the *data* they have been *trained on*. Unlike traditional AI systems that are designed to *recognise patterns and make predictions*, generative AI *creates new content* in the form of images, text, audio" or video (italics added, WEF, no date)[4]. Thus, we find examples such as Chat GPT and Google's Bard that claim to create new text content. DALLE, Stable Diffusion, and MidJourney are examples of generative AI that creates images from text inputs. There are AI applications that can also produce video and sound from text inputs.

With the release of Chat GPT 4 and other newer iterations of generative AI, multimodal inputs and outputs can be managed. For example, Chat GPT 4 can take both text and images as inputs to respond in text to our prompts or queries. Generative AI can also be used in organisational workflows and tasks. See the below examples from Google and Microsoft on how they are leveraging generative AI in their user applications and how we can use these capabilities in daily work and tasks.

How Google is leveraging generative AI for its Workspace applications: **Click Here**

Microsoft's introduction of Copilot to leverage generative AI for its Office applications:**Click Here**

Click Here

The generative models and algorithms are said to 'learn'[5]. There are two types of 'learning' in machine learning: supervised and unsupervised learning. As the name entails, supervised learning is where a human assists the AI model to learn. For example, a human assists the AI model with differentiating features of animals or objects for the AI model to successfully categorise new inputs of animals or objects. Unsupervised learning is where the AI model sifts through the training data and identifies patterns, through mathematical or statistical methods, that it uses in this example to classify animals or objects.

See the following video on difference between supervised and unsupervised learning: **Click Here**

Chat GPT is a Large Language Model (LLM) generative AI. It was developed by Open AI, which is now in a partnership with Microsoft. The description 'large language models' refer to the large text datasets the model is trained on and the internal configuration (or the parameters of the artificial neural network) of the model that can be changed. These data can be public text accessed and drawn from the world wide web.

1. For an illustration of the multilayers, see the figures in the later section on definitional issues.
2. **https://www.linkedin.com/pulse/future-ai-part-v-cutting-edge-imtiaz-adam**
3. See the discussion later in the Fact Sheet on definitions of AI for a discussion on what abilities we attribute to machines or AI.
4. **https://www.weforum.org/agenda/2023/02/generative-ai-explain-algorithms-work**
5. See the section on definitional issues on ascribing human abilities to machines or using human intelligence as the benchmark for possible forms of intelligence.

Chat GPT

> Large language models are, generally speaking, tens of gigabytes in size and trained on enormous amounts of text data, sometimes at the petabyte scale. They're also among the biggest models in terms of parameter count, where a "parameter" refers to a value the model can change independently as it learns. Parameters are the parts of the model learned from historical training data and essentially define the skill of the model on a problem, such as generating text.[6],[7]

> In June 2020, AI startup OpenAI released GPT-3, a 175 billion-parameter model [...][8] and trained on "570GB of data obtained from books, web-texts, Wikipedia, articles and other pieces of writing on the internet[, which is about] 300 billion words.[9]

> Trained using troves of internet data, these machine-learning models take a small bit of input text and then predict the text that is likely to come next.[10]

Is the prediction by the model classifiable as learning or the creation of something novel? Or is it repeating patterns identified in the large data sets it was trained on?

> GPT-3 has hundreds of billions of parameters and was trained by reading huge swaths of text on the internet, from Wikipedia articles to Reddit posts. So, when someone shows the model examples of a new task, it has likely already seen something very similar because its training dataset included text from billions of websites. It repeats patterns it has seen during training, rather than learning to perform new tasks.[11]

6. **https://techcrunch.com/2022/04/28/the-emerging-types-of-language-models-and-why-they-matter/**
7. See the intriguing idea of models developed within models by the AI model: **https://news.mit.edu/2023/large-language-models-in-context-learning-0207**
8. **https://techcrunch.com/2022/04/28/the-emerging-types-of-language-models-and-why-they-matter/**
9. **https://www.sciencefocus.com/future-technology/gpt-3/**
10. **https://news.mit.edu/2023/large-language-models-in-context-learning-0207**
11. **https://news.mit.edu/2023/large-language-models-in-context-learning-0207**

"[Rather than learning] perhaps these [..] models have smaller machine-learning models inside them that the models can train to complete a new task.

GPT stands for generative pre-trained transformers. This means the transformer technology or machine learning model is pre-trained on large data sets. The transformer comprises of mathematical techniques to track relationships in the data and is thereby said to be able to analyse and respond to context and the variable meanings of words in these contexts.

Before transformers arrived, users had to train neural networks with large, labeled datasets that were costly and time-consuming to produce [see the previous video on supervised and unsupervised learning]. By finding patterns between elements mathematically, transformers eliminate that need, making available the trillions of images and petabytes of text data on the web and in corporate databases. [12]

See the following video outlining what a transformer is: **Click Here**

For a more technical explanation that shows some of the mathematical techniques used, see the following video: **Click Here**

Chat GPT is a generative pre-trained transformer that allows for input and outputs in a conversational or chat format. As with other generative pre-trained transformers, such as Google's Language Model for Dialogue Applications (LaMDA) and its rival Chat GPT offering named Bard, it uses mathematical techniques to track relationships in the inputs, recognise patterns and thereby predict the likely output. "As a language model, it works on probability, able to guess what the next word should be in a sentence" [13]

See the following video on what GPT means and applications and limitations thereof: **Click Here**

Then see this video on how transformers are used in Chat GPT: **Click Here**

12. **https://blogs.nvidia.com/blog/2022/03/25/what-is-a-transformer-model/**
13. **https://www.sciencefocus.com/future-technology/gpt-3/**

Chat GPT 4, the latest iteration of the generative pre-trained transformer by Open AI, is multimodal. This means it can accept text and image inputs. Chat GPT 3 was limited to text inputs. However, it seduced us with "an impressive ability to string sentences together" . However, as noted by Perrigo, it was "also prone to blurting out violent, sexist and racist remarks" (ibid). The vast public data of the world wide web it was trained on "was the reason for GPT-3's impressive linguistic capabilities, but was also perhaps its biggest curse. Since parts of the internet are replete with toxicity and bias, there was no easy way of purging those sections of the training data" (ibid). Perrigo's investigation suggests that an outsourcing firm in Kenya helped the AI model identify and detect these forms of toxic and biased behaviour. The workers in Kenya were paid a minimal two US dollars an hour to label "examples of violence, hate speech, and sexual abuse" (ibid). It shows the hidden labour and disparate pay between the developed and developing world in the development of AI applications. Apart from this semi-supervised learning of Chat GPT and before, other supervised learning helped to fine tune the language model.

It is important to note that ChatGPT is not able to search the internet for information. "It uses the information it learned from training data to generate a response, which leaves room for error"[14]. For example, Chat GPT 3 had access to open information until 2021. Google's Bard and Microsoft's Bing applications are experimenting with incorporating the generative AI and internet search. There are other examples currently available as well.

Another limitation of Chat GPT and other generative AI is the ability to understand meaning and make sense of the world. It uses mathematical techniques to work out probabilities and predict the likely strings of words in response. As Ortiz states, "critics argue that these tools are just very good at putting words into an order that makes sense from a statistical point of view, but they cannot understand the meaning or know whether the statements it makes are correct" [15]. A related limitation is that AI models may 'hallucinate', which means it generates an output or response to an input that has no basis in reality. Thus, there can be "mistakes in the generated text that are semantically or syntactically plausible but are in fact incorrect or nonsensical"[16]. This can lead to misinformation that is produced by language models or the creation of fantastical or realistic but false images by image generating AIs.

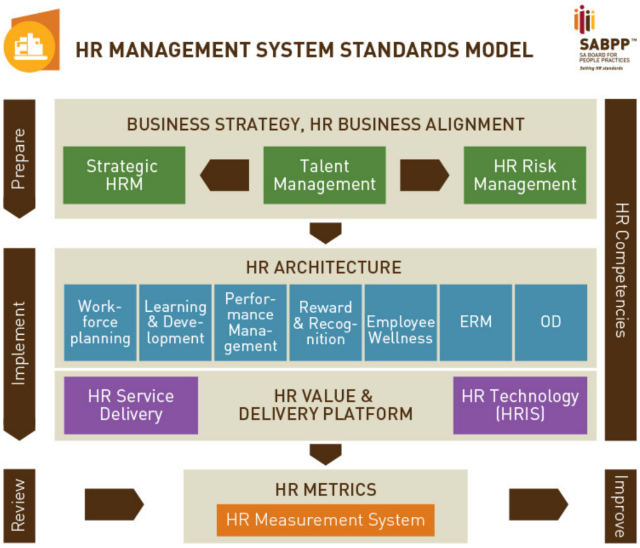
Where could HR use generative AI?

It is important that we keep in mind the limitations of generative AI such as Chat GPT when we explore the opportunities and various uses of it. Some of the opportunities and uses of Generative AI in HR can stem from leveraging its capabilities in context which include:

- interactive and conversational interface and abilities
- pretrained large language model
- ability to take in large amounts of text inputs
- ability to 'learn' from inputs and feedback as outputs
- pattern recognition and prediction abilities
- create content from existing or pretrained data
- summarise or explain content in a requested form (for example, asking Chat GPT to explain quantum physics to a five-year-old)

These capabilities can be leveraged across the employee lifecycle. It can assist with the 'back end' and 'front end' of people practices across the lifecycle, from onboarding to development, career, performance, and exit management. The capabilities can also be leveraged to work through the SABPP System Standards Model, from strategy formulation and alignment and developing the HR architecture to enabling the HR value and delivery platform and HR measurement platform. Examples are provided in the below graphic.

14. https://www.zdnet.com/article/what-is-chatgpt-and-why-does-it-matter-heres-everything-you-need-to-know/
15. https://www.zdnet.com/article/what-is-chatgpt-and-why-does-it-matter-heres-everything-you-need-to-know/
16. https://spectrum.ieee.org/ai-hallucination



We can consider for example the:

- processing, indexing, and creation of content throughout the HR value chain – from strategies, policies, advisories, and process flows, to management reports.
- curating and customising content for learning, development, wellbeing, and performance
- manage text and verbal queries and provide text or audio-based responses to it
- provision of HR self-service and chatbot when and as needed by employees and managers
- drawing out trends and themes across a vast array of HR and organisational communication and data
- reports and communication aide

Bersin (2023), for example, outlines the creation of content throughout the HR architecture given that much HR information is textual[17] . For example, creating content for job and competency profiles, onboarding, and learning and development. Consider the possibility of generating case studies, simulations, assignments, and assessment aides for learning and development, including coaching and learning in the flow of work. However, we should remember that it is creating content based off past data or content. Another example is indexing or summarising employee reports for performance management. Relatedly, we could consider the example of building personal development plans or skills development plans based on the summarised performance reports. This opens up opportunities for coaching by a generative AI or the use of it to motivate, track, and evaluate learning and development progress and outcomes.

Generative AI could also be leveraged for HR self-service. One example is a chat bot. Here, we can see the application of Chat GPT and other generative AI as a chat bot for various HR processes, from developmental and transactional HR services delivered to existing employees to recruitment of talent both internally and externally. Consider how generative AI can assist with the development of a talent marketplace, from identifying and engaging to sifting, appointing, and contracting talent for various positions or work assignments[18]. Another example could be the integration into people analytics or talent intelligence platforms. This means leveraging the AI in terms of feeding into, integrating with, and/or extracting from other HR and business platforms. Thus, it could assist with strategy formulation by analysing and reporting on external environment trends or themes as well as internal environment trends or themes. It could also assist with and enable strategy execution and provide the analytics and talent and business intelligence required for this. It can be leveraged in work flows and tasks as Microsoft's use of generative AI such as Chat GPT in their applications. This confronts us with the need to rethink how work is currently done and how it will be done in the future, and what are the human and technology capabilities required in organisations for this in the present and future.

17. See the details of Bersin's suggestions here: **https://joshbersin.com/2023/03/the-role-of-generative-ai-and-large-language-models-in-hr/.**
18. See the September 2021 Fact Sheet: **https://cct.mycpd.co.za/SABPP/FactSheets/2021/fact_sheet_sep_2021.pdf**

Available examples suggested for the use of Chat GPT and other generative AI in HR

By Di Meglio (2023)[19]

- *Recruiting and Hiring*
  assist with resume screening, candidate questions, and scheduling interviews.
- *Employee Onboarding*
  provide new hires with information on company policies, benefits, and procedures.
- *Employee Engagement*
  use for pulse surveys, employee feedback, and suggestion boxes.
- *Performance Evaluation*
  help with the preparation of performance reviews, collecting feedback from colleagues, and setting goals.
- *Training and Development*
  assist with the delivery of training materials, answering employee questions, and tracking training completion.
- *Compliance and Policy*
  provide employees with information on company policies and compliance requirements, and answer related questions.
- *HR Data Management*
  assist with data entry, employee records management, and generating reports.
- *Employee Assistance*
  provide employees with support and resources on work-life balance, mental health, and other personal issues.
- *Diversity and Inclusion*
  assist with the creation of diversity and inclusion programs, tracking progress, and answering employee questions."

Generative AI will have profound implications for HR. This includes preparing the organisation and its talent for it and to use it effectively, efficiently, and economically. It also includes investigating how AI can augment and advance, but also how it may substitute or replace human judgment, effort, and work or task completion. Here, we could consider the debate on the shift from jobs to skills-based project teams, assignments, and roles (**see the February 2021 Fact Sheet on reinventing work and jobs**).

Speaking of work and task completion, one of the issues organisations need to navigate is how their employees and workers are currently utilising Chat GPT and other AI applications in their work. And whether they are using it in a 'copy and paste' fashion or in a deliberate and critical manner that is mindful of the limitations and capabilities of AI. These are some of the tricky questions we need to engage with. Is the use of AI a form of plagiarism or cheating when used to complete whole aspects of work and learning assignments? Is it plagiarism or cheating if used verbatim for examinations such as school, university, or professional body examinations?

See this snippet from an interview with Noam Chomsky, who is says Chat GPT and other generative AI can be a useful tool but these are also 'high tech plagiarism' and a 'way of avoiding learning'[20] **Click Here**

Consider his criticism of viewing the brain as a computer or artificial neural networks.For a longer form interview see: **Click Here**

We could consider innovative uses of AI where learners are deliberately asked to use AI and, importantly, asked to evaluate the generated response by the AI and develop a critical position on the subject at hand. This then explores how human learning and work can be augmented through and by technology such as AI, and how humans, machines, and AI can work together and be leveraged for realising organisational and social objectives.

19. **https://www.hrexchangenetwork.com/hr-talent-management/articles/9-hr-jobs-chatgpt-says-it-can-do**
20. **https://indianexpress.com/article/explained/explained-sci-tech/chatgpt-is-basically-high-tech-plagiarism-what-noam-chomsky-said-about-the-controversial- chatbot-8442784/**

See the following article on the debate on whether Chat GPT 'really passed' a MBA exam that a Business School professor submitted to the AI for a response. And how the AI's responses change depending on the prompt given: **Click Here**

A way organisations and other institutions can identify the use of AI is to use AI to detect AI. See the example of GPTZero which was designed to detect the use of AI: **Click Here**

See the tool Open AI launched to differentiate AI and human-written text: **Click Here**

Ethics, governance, risk, and compliance

As we consider the practical applications of generative AI, we need to also attend to the important debates on AI ethics, governance, risk, and compliance with legislation, regulations, and organisational policies. One of the critical themes in the discussion is the biases in the AI models that stem from the biases in the training data and the AI design and coding team. Another theme is the alignment problem. That is, the question of whether AI models are aligned with our human purposes and values (Christian, 2020). Related to these themes is the call for explainable AI:

> Explainable artificial intelligence (XAI) is a set of processes and methods that allows human users to comprehend and trust the results and output created by machine learning algorithms. Explainable AI is used to describe an AI model, its expected impact and potential biases. It helps characterize model accuracy, fairness, transparency and outcomes in AI-powered decision making. Explainable AI is crucial for an organization in building trust and confidence when putting AI models into production. AI explainability also helps an organization adopt a responsible approach to AI development[21]

The crucial question seems to be who is accountable for the AI models and the judgements or decisions made by these models. For example, if AI is used to make talent selection decisions, then who is accountable to ensure procedural and substantive fairness and that adverse impact is monitored and addressed. See this CIPD article on using AI responsibly, which reports on a survey results on the use of AI: **Click Here**. Organisations need to consider the privacy and safety of users and the individuals represented or referenced in the AI application's data. They need to also consider the 'guardrails' required to limit the elicitation of biased, toxic and harmful responses from AI applications as well as inadvertent release of individuals or institutions' private data by the AI through hacks or other surreptitious prompting by bad actors.

In engaging with the above issues, we need to understand what abilities we attribute to AI and what organisational decision-making and processes are allocated to it. This means we need to critically evaluate definitions of AI, the assumptions informing analogies between humans (or rather human brains and cognition) and machines or AI, and attribution of abilities such as learning, thinking, judging, evaluating, and considering multiple perspectives and implications. In the next section we outline some of the definitional issues and what human intelligence is and what is ascribed as machine intelligence. It is not a comprehensive survey of the different fields of study such as cognitive psychology, intelligence measurement, and computer science.

21. **https://www.ibm.com/watson/explainable-ai**

Ethical considerations of AI for HR
By Yael Dall, Discovery, Group Ethics Office

Bias & Discrimination

- AI systems are unbiased, however if data contains biases, AI perpetuates biases.
- Results in discriminatory hiring practices, exclusion of certain groups.
- Ensure data used to train AI systems is diverse and representative of different groups.
- Use tools to test and audit AI system for bias, make adjustments
- Ensure HR policies & practices designed to be inclusive and non-discriminatory.

Privacy

- AI systems require access to personal info about applicants & employees.
- Raises concerns about privacy and data protection.
- Requires safeguards to protect data from misuse & unauthorised access.
- Implement data protection measures: encryption, access controls, secure storage.
- Be transparent re data collected, how used, provide clear information re employee rights.

Transparency

- AI can be unclear, difficult to understand, challenging to ensure makes fair, unbiased selections.
- Explainability of AI "black box" concerns.
- No access to training data set to know what's in the data to enable identification what's missing.
- Requires transparency about how using AI in HR processes, ensuring criteria used to evaluate job applicants are clear, well-defined, and employees & job applicants understand criteria.
- Provide opportunities for employees & job applicants to ask questions, provide feedback.

Accountability

- Responsibility for decisions made by AI systems.
- Address any negative consequences.
- Requires robust monitoring & evaluation to ensure functioning as intended.
- Ensure accountability by monitoring & evaluating AI and adjusting as needed.
- Process in place for employees & job applicants to raise concerns and provide feedback.

Job Displacement

- As AI becomes more advanced, risk of replacing certain human tasks, redeployment of resources.
- Consider social and economic impact of introducing AI into HR processes.
- Mitigate risk of job displacement by developing strategies to reskill and upskill employees whose roles/ tasks may be affected by AI systems.
- Explore new roles & opportunities, engage with employees about impact of AI.

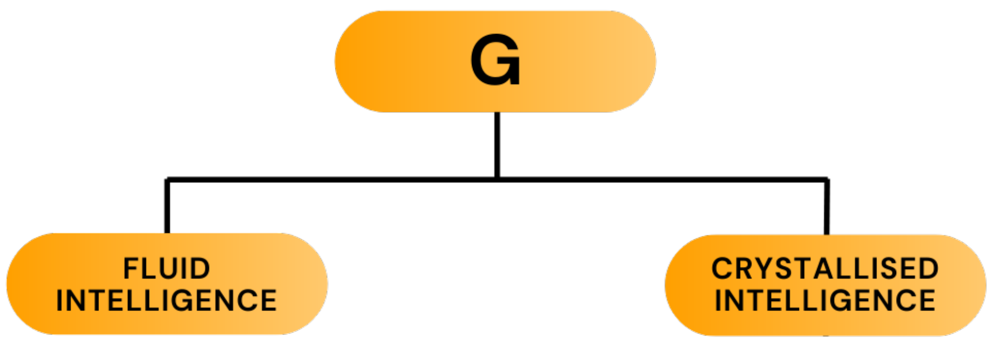
Definitional issues with AI

We need to understand what AI is – or rather what we claim AI to be. Most times we find AI is defined in relation to human beings or human intelligence. Thus, we will first briefly outline how human intelligence is defined and then explore the way artificial intelligence is defined. However, we should note that the two fields of human and artificial intelligence develop separately, with some developing computer models to simulate and explain our biological brains and others using our brains or our human cognition as models that form the basis for developing machine learning and behaviour.

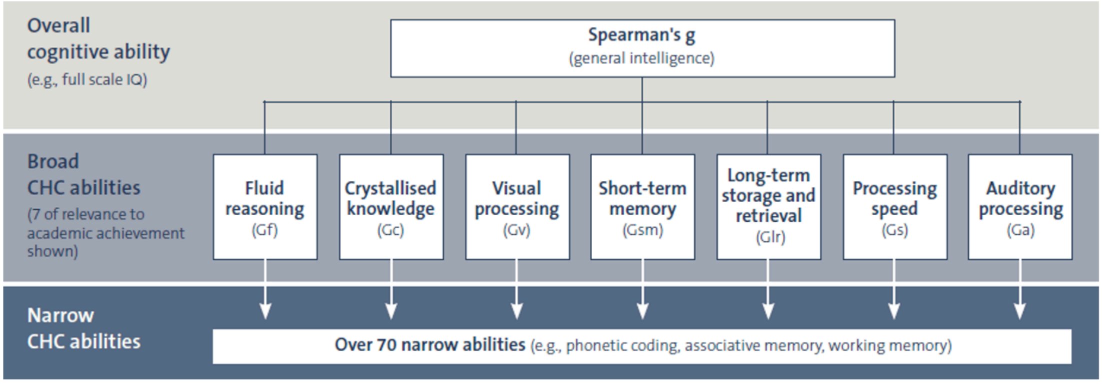
As will be seen there are no clear agreements in both separate fields on what is human and artificial intelligence. There are even contestations regarding these very phenomena, calling these into question and subsequently their definitions. Thus, there are contrasting or conflicting philosophical and theoretical assumptions informing different approaches. The below is not a comprehensive summary of the fields of intelligence, but rather serve as points of entry into the fields for further exploration and questioning.

Human Intelligence

There are continuing theoretical and empirical debates regarding human intelligence (Brown, 2016; Sternberg, Nokes, Geissler, Prince, Okatcha, Bundy, Grigorenko, 2001; Ziegler, Danay, Heene, Asendorpf, & Bühner, 2012). These include contestations on what intelligence is. For example, there are questions on whether intelligence is an underlying and singular individual trait. This stems from debates in the intelligence measurement or psychometric field on whether we can infer a single or multiple factors of intelligence. The singular factor is referred to as the 'g' or general factor – at times it is referred to as Spearman's G as a reference to Spearman who advocated for a general factor. The G factor is said to influence various specific cognitive processes. One representation of the general factor is a hierarchical model, as illustrated below, where G comprises of fluid and crystallised intelligence that influences specific cognitive processes. **Fluid intelligence** is the ability to perceive relationships or patterns that are independent of previous learning or experience. While **crystallised intelligence** refers to accumulated knowledge from previous learning and experience and its use.

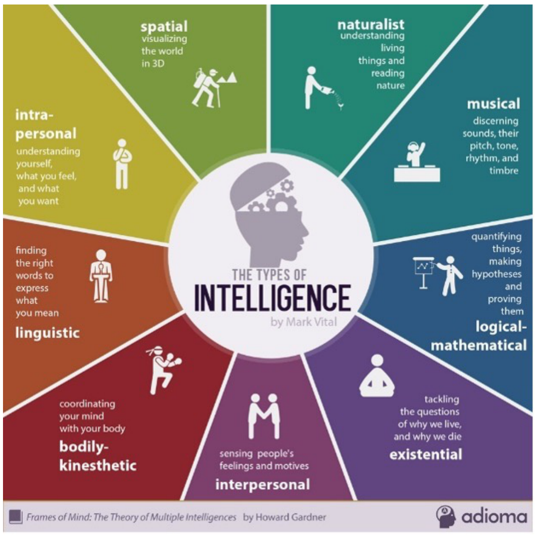


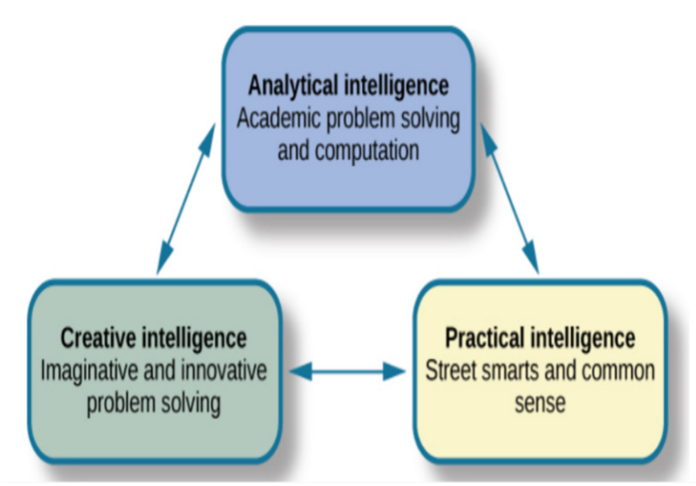
A more elaborate model developed by the Cattell–Horn–Carroll theory (CHC) suggest three levels of abilities: **general** ability, **broad** abilities, and **narrow** abilities. These are illustrated below. The broad and narrow abilities entail different forms of reasoning, processing, knowledge. We can note the reference to fluid and crystalised abilities in CHC theory as well.



Source: **APS (no date)**

Other models propose **alternate conceptualisations** of intelligence, suggesting different ways of thinking about multiple factors, intelligences, or abilities. Below left is an illustration of Gardner's multiple intelligence model and the right the illustration of Sternberg's triachic theory of intelligence. Here we can note the theoretical developments in cognitive and neuropsychology as well as human developmental theory and neuroscience apart from the previously discussed psychometric approach to intelligence.





Source: **TLC (no date)**

Source: **UCF (no date)**

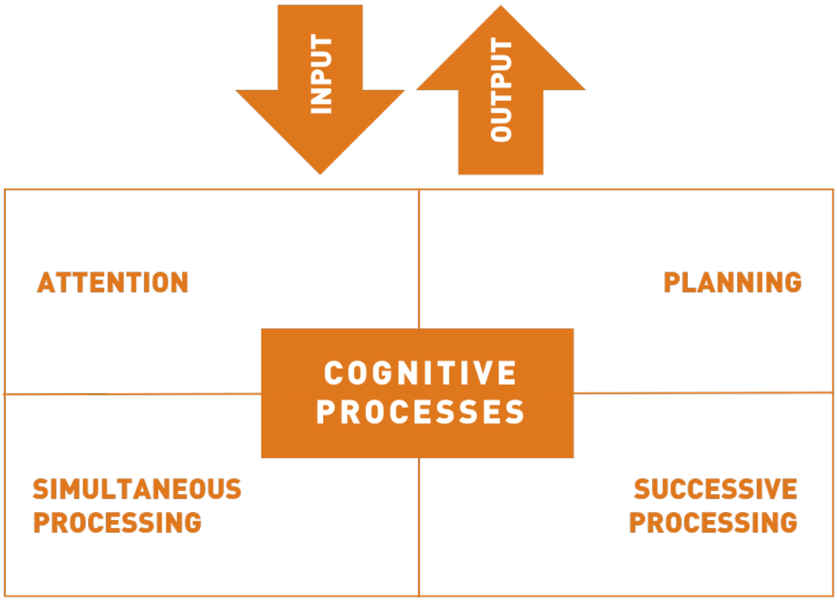
The range of views of intelligence leads to various definitions of it – and important theoretical and empirical contestations, especially when intelligence is associated with, or related to, social group level phenomena and racial and gender stereotypes. A general definition is provided by the American Psychological Association: "the ability to derive information, learn from experience, adapt to the environment, understand, and correctly utilize thought and reason"[22]. We can note here that the different models may focus on and incorporate specific aspects of these abilities in their definition based on their theoretical assumptions. Sternberg and Detterman (1986) propose the following definition:

22. **https://dictionary.apa.org/intelligence**

"person's ability to adapt to the environment and to learn from experience". Sternberg (2005) unpacks this definition as follows:

- the *ability* to achieve one's *goals* in life, given one's *sociocultural* context;
- by capitalizing on strengths and *correcting* or *compensating* for *weaknesses*;
- in order to *adapt* to, *shape*, and *select environments*;
- and, through a *combination* of analytical, creative, and practical abilities"

When we think about comparing human and artificial or machine intelligence, we need to critically examine what and how are we comparing – we also need to think about why we are comparing and what assumptions inform the comparisons made. A model that we could use to help examine what and how we are comparing is the Planning, Attention, Simultaneous, and Successive (PASS) model of intelligence, presented as an alternative to general ability models of intelligence (Das, 2002). The model delineates the cognitive processes of planning, attention, simultaneous processing of different stimuli, and successive or linear order processing of stimuli. It is illustrated below.

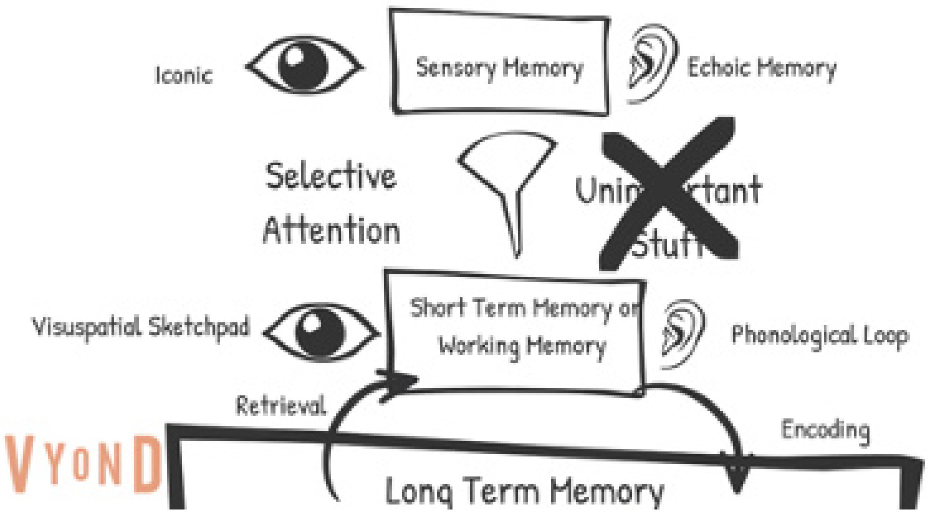


Source: Adapted from Das (2002)

Moving beyond intelligence theory and research, we could look at information processing theory in cognitive psychology. Here, one finds models of how humans receive, seek, store, process, transform, and communicate information. We also find analogies between humans and computers or machines in that the same processes are assumed to underlie human and computer or machine information processing.

See the following video break down the components and processes of information processing (see the screenshot below). Note in the beginning the point on the analogy that the brain is like a computer.

Click Here



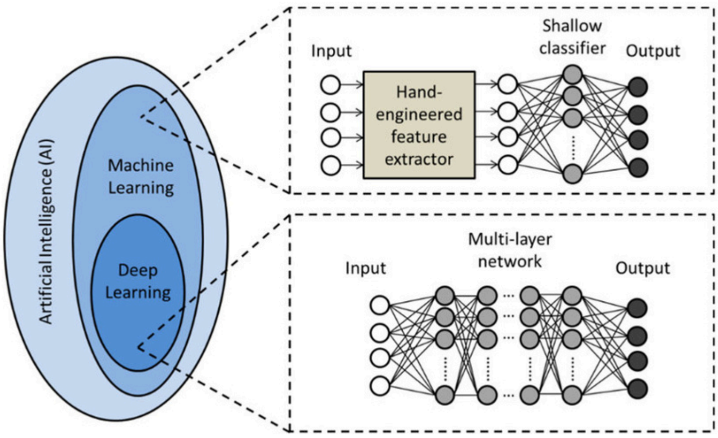
Artificial intelligence (AI)

There are contestations regarding the definition of AI – including whether we should use the term 'intelligence' (Mitchell, 2019). One definitional example is from an IBM resource: "artificial intelligence leverages computers and machines to mimic the problem-solving and decision-making capabilities of the human mind" [23]. Here, we see the link drawn to human intelligence and we can note that various definitions either suggest mimicking, simulating, or creating human intelligence.

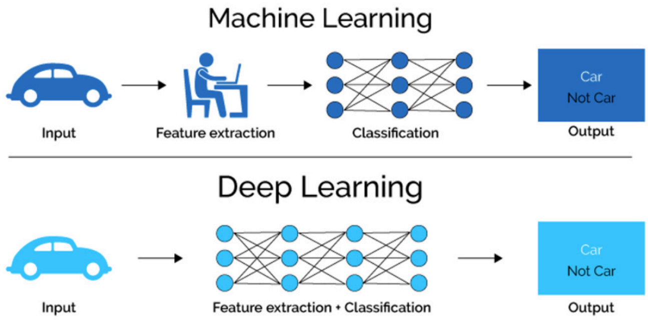
The IBM resource also cites the definition by John McCarthy (2007): "It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable" (p2). McCarthy defines intelligence as the "computational part of the ability to achieve goals in the world" (italics added, ibid); adding that "varying kinds and degrees of intelligence occur in people, many animals and some machines" (ibid). We can note that there is some similarity with Sternberg's definition of intelligence, which was presented in the previous section regarding adapting to the environment. More importantly, we can note that McCarthy broadens the investigation of intelligence and does not limit it to humans.

23. **https://www.ibm.com/topics/artificial-intelligence**

One attempt by those in the AI field to define AI is as follows: *"a branch of computer science that studies the properties of intelligence by synthesizing intelligence"* (italics added, Mitchell, 2019, p7). We can see the subtle shift from mimicking to synthesising intelligence. Mitchell states that on a *"practical side, AI proponents simply want to create computer programs (sic) that perform tasks as well as or better than humans, without worrying about whether these programs (sic) are actually thinking in the way humans think*" (italics in original, ibid). Which brings us to the question on how the field of AI defines or thinks about learning, reasoning, thinking, and evaluating. Can the pattern recognition through mathematical or statistical methods count as learning, reasoning, or thinking? For example, compare the below two illustrations, along with the illustration of transformers in the cited videos earlier, with the PASS model of human intelligence. However, this may be too a simplistic framing of the problem; and the comparisons of simplified illustrations may be deceptive and problematic. Even using the concepts of fluid and crystallised intelligence to compare, or draw analogies between, human and machine learning may be helpful to a point but also problematic.



Source: Boon, Joshi, Bhudolia, & Gohel (2020)



Source: Cadavid, Lamouri, & Grabot (2018)

See the IBM video resource on applying fluid and crystallised intelligence concepts to machine learning: **Click Here**

There are complex web of concepts and assumptions from diverse fields of study involved in the research on human and machine intelligence, cognition, processing, language, and decision-making. And these various fields do not always interact or integrate. We also need to consider the fields of study that look at human information processing, human neural networks, and the brain functioning in a holistic way. That is, looking at these from the perspectives of cognitive, emotional and social functioning and how humans as embodied beings navigate and make sense of the world and adapt to their environment and socio-cultural context. This returns us to Sternberg's triachic model of analytical, creative and practical intelligence. It also confronts us with the need to consider various forms of these intelligence – in humans, animals and machines. We also need to consider that there are different approaches to AI that have evolved over time. That is, Symbolic AI and Connectionist AI. We have been discussing machine learning and neural networks thus far, which are examples of connectionist AI. There is no prior knowledge required by the AI as it identifies associations or patterns in the data through its training. In Symbolic AI, knowledge needs to be coded and represented in symbolic terms in the AI application first as well as rules for reasoning or making inferences from these symbols. Examples of symbolic AI are the earlier expert systems. Usually, humans code the symbolic AI applications and are able to explain how the AI works (refer back to the earlier point in the previous section on explainable AI).

See the following video that shows the symbolic AI approach and the contrast to a connectionist approach: **Click Here**

A Way Forward

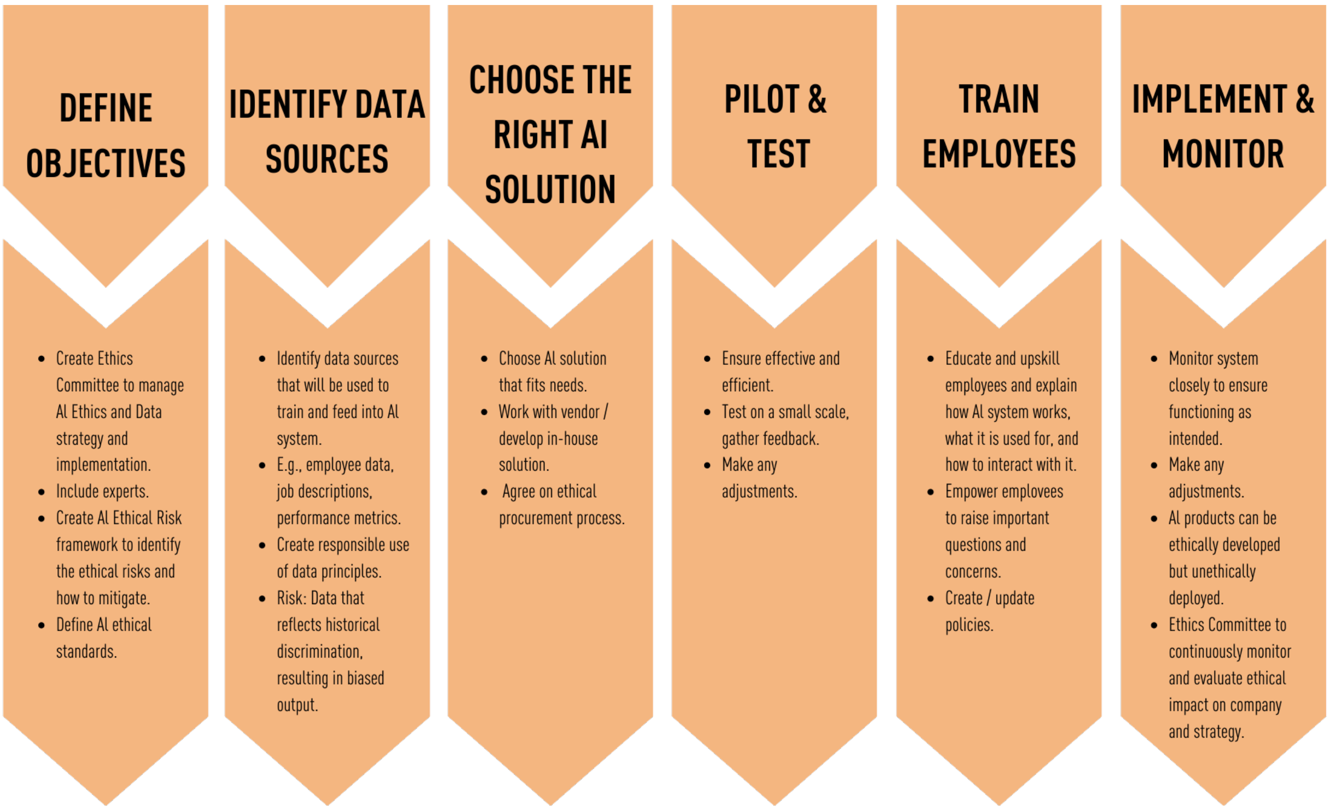
AI applications can certainly be productive tools that can be used for specific tasks. The key question is how we use it. This includes the various examples of its use in HR and the impacts and implications thereof as well as unintended consequences. However, we should note that AI applications are not seen and used simply as tools. There are attributions and inferences made regarding AI capabilities. This includes abilities such as learning, thinking, creating, reasoning, judging, evaluating, and decision-making. There are also analogies or similarities drawn between humans and machines or AI in terms of intelligence, cognition, and information processing. These are informed by specific philosophical and theoretical assumptions. These analogies and similarities are contested from alternate conceptual frameworks. We need to also consider the ethics, governance, risk, and compliance issues with the use of AI. And we need to be vigilant that we do not abdicate – explicitly or tacitly – our responsibilities, our impact on others, and our ethical duty to AI.

What is the way forward? First, we need to have a strategic and holistic understanding of our evolving context and the profound effect of trends therein on people practices in the future. In the **October 2022 Fact Sheet** we identified the following themes to understand our evolving context and future trends:

- holding the purpose in an ever-changing world, which points to the increasing importance of good governance in organisational sustainability
- embracing the future which means engaging and shaping the future world of work holistically, including the fourth industrial revolution, Web 3.0, metaverse, and other disruptive or exponential technologies such as generative AI
- overcoming exclusion, inequity (including the digital divide), and discrimination in the present and future
- and building into a green, crisis-resilient, and sustainable future

We recommended that the above contextual themes should be viewed and considered from a people-centred perspective to the future world of work and the use and implementation of technologies. This includes generative AI.

Given this understanding of our evolving context through the identified themes, we can now work through how we can embrace and implement AI. Below is an illustrative example by Yael Dall, from Discovery's Group Ethics Office, of how we could take an organisation-wide and systematic approach to embracing and implementing AI.



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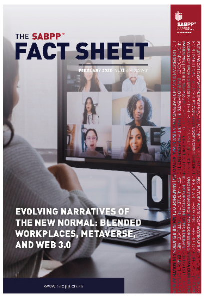

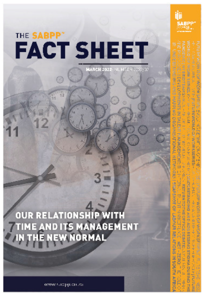

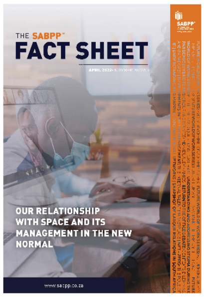

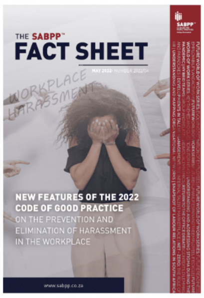

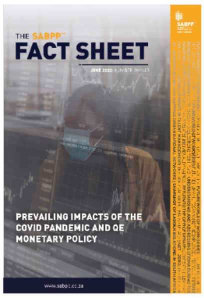

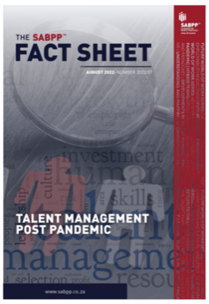

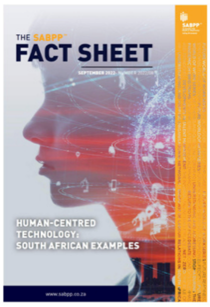

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