Artificial intelligence – prerequisites for competent use and assessment

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The author explains which computer systems form the basis of artificial intelligence and how AI influences media pedagogical work and our understanding of media literacy.

The discussion about artificial intelligence (AI) in relation to schooling, learning and education experienced a fulminant upswing with the release of the chatbot *ChatGPT* at the end of 2022. However, a revolution in learning through AI has long been predicted, e.g. in the early 2000s: "This next revolution will be based on the widespread use of artificial intelligence in educational technology (…)." (Forbus & Feltovich, 2001, p. 3; see also Herzig, 2020a) However, this development has largely failed to materialise; AI has not become established in the educational context, especially in schools, apart from individual applications of so-called intelligent tutorial systems (Rietz & Völmicke, 2020). The enormous and immediate response to *ChatGPT* can be attributed in particular to its low-threshold, browser-based accessibility, its control via natural language input, and the breadth of its content. This could quickly lead to the assumption that there are only a few challenges for competent use. A closer look at (generative) AI shows that this is a misleading assumption.

AI – PROBLEM SOLVING WITH RULES AND EXPERIENCE

Artificial intelligence refers to IT systems that perform tasks requiring some form of thinking or intelligence in humans. Such tasks or requirements include, for example, drawing conclusions, learning from experience, making decisions and predictions, or reacting appropriately to situations (Hwang et al., 2020). AI can simulate such cognitive abilities in 2 ways: in so-called symbolic AI, the thought processes required for a task are modelled and programmed as a system of rules. One example is intelligent tutorial systems (also known as expert systems), in which specific specialist (expert) knowledge is modelled (knowledge model, e.g., orthographic knowledge and associated rules), a so-called learner model (e.g., typical errors and error concepts of students), and didactic instructions (teaching model, e.g., on learning activities for certain errors). A system modelled in this way can recognise individual errors and then give hints on which information or action should be carried out in order to improve the corresponding competence. As such systems are limited to specific mathematical, scientific, and linguistic areas and are costly to produce, they have not become widespread in schools.

Machine learning methods take a different approach. In these cases, so-called learning algorithms also follow rules, although these do not yet contain a concrete (rule-based) solution to the problem. Instead, they specify how the algorithm can learn from experience to solve the problem. The experience basis for these processes is provided by large amounts of (training) data. Machine learning has an important application in generative AI.

GENERATIVE AI – PROBLEM SOLVING WITH NEURAL NETWORKS AND LANGUAGE MODELS

Generative AI – as used in chatbots such as *ChatGPT* – is characterised by the fact that it generates data sets that are very similar to human language on the basis of an input. This is done using language models, which basically work as follows: the language model learns the "meaning" of a word by learning in which contexts a word occurs based on training data. When an input is processed, the model successively calculates for all words in the input which word would most likely follow the respective input word, based on the (previously learnt) occurrences and the relationships between these words in the training data. The language model therefore does not work with a knowledge-based system, but with probabilities, i.e., stochastic processes. The pre-trained learning processes as well as the processing of a specific input are realised with neural networks in which "thought processes" are simulated with artificial neurons. Processing an input means changing the parameters of these neurons (the weights of the input and when they transmit signals to subsequent neurons in the network) until the statistically most probable result is achieved. The input is passed through various layers of the network, which can contain several hundred billion parameters (deep learning). The result of the "learning process" is then available in the form of a specific con-

figuration of the network's parameters. However, as the individual layers of the network are not visible, the specific solution – in comparison to symbolic AI – is not comprehensible to humans (a "black box").
The functionality of generative AI, which has only been outlined here, has media pedagogical consequences for both learning with and learning about AI, i.e., for questions relating to media didactics and media education.

LEARNING WITH GENERATIVE AI

Generative AI can be used to process tasks that are typical for learning activities, e.g., the creation of texts in different genres (e.g., non-fictional and fictional texts, source texts for programming, instructions), the analysis and evaluation of texts (e.g., orthographic analysis of text, interpretation of mathematical formulae), and the modification of text (e.g., linguistic simplification, translation). These tasks can be delegated to a chatbot as input in the form of so-called prompts, whereby the prompts have a significant influence on the results. Prompts are effective if they provide contextual information (e.g., the role that the chatbot is to assume or the presentation of a specific initial situation), contain concrete instructions (e.g., the creation of an application letter), include additional information to be considered (e.g., a CV or information about a company), and specify the desired result format (e.g., a cover letter in mail or classic letter format of a certain length) (Ozdemir, 2024).
The use of generative AI is, of course, associated with the risk of avoiding learning activities oneself by adopting finished products, thereby bypassing the learning process. A chatbot shows its real strength for learning when it is used as a dialogue system. As a learning companion, the chatbot can, for example, explain facts, provide feed-

Ill. 1: Media education with AI in primary schools: raising awareness of the AI-based design of images[1]

back, formulate individual assistance, or conduct dialogues in foreign languages. For instance, the chatbot can be asked to output all the solution steps of a mathematical task individually ("chain of thought prompting"; Wei et al., 2022), or instructed to present the learner with subtasks step by step, wait for them to be solved, evaluate them and, if necessary, provide further help in solving them. In terms of creativity, generative AI is limited because it is restricted to its training data and, although it generates correlations from this data that are new or surprising for the user, it is not creative in the true sense of the word (see also Rotsch in this issue). However, it can provide inspiration and input for creative human processes.
In terms of learning theory, generative AI is not a revolution in learning because learning remains an active, independent, strenuous, socially embedded process that cannot be delegated. However, this process can be significantly enriched and supported by generative AI. To achieve this, learners must be able to recognise their own need for information or support, formulate targeted prompts, and use dialogue skills to promote learning – against the background of existing knowledge and skills. In addition, certain requirements emerge when (generative) AI itself becomes the object of learning.

LEARNING ABOUT (GENERATIVE) AI

Generative AI is based on language models that are both pre-trained and further trained with input and feedback from users. The quality of the results therefore depends significantly on the training data used. If there are biases in the training data, these are incorporated into the results and may be amplified by the system (see also Coutant & Cortina in this issue). Another issue is that language models do not provide reliable results for specific subjects or domains but are rather generalists. When in

doubt, the model may hallucinate and produce output that sounds linguistically plausible but is factually incorrect or even nonsensical. This highlights that, although using a language model is low-threshold in terms of handling, it is extremely demanding in terms of assessing the results.
In the public discussion about *ChatGPT*, legal aspects also play a major role. If it is no longer possible to decide whether a text was created by AI or by a person, the question arises as to what extent such products can still be the subject of performance assessment, for example. In addition, the question of authorship arises when the products of a generative AI include both the prompts and the training data (Horn, 2023).

Media education issues and ethical questions arise

When considering generative AI in a broader context, it becomes clear that it affects many everyday situations, raising further media education issues. Machine learning methods are suitable for recognising correlations, patterns, and structures in large amounts of data (big data) and making predictions, recommendations, or decisions on this basis. The underlying data is partly provided by the users themselves, e.g., when visiting websites or using (learning) platforms, and partly collected via sensors or statistics – although this is not always disclosed (Herzig et al., 2022). AI can evaluate such data and use it for personalised recommendations of media offerings or consumer goods, for individual risk assessment when granting loans, for predicting crime (predictive policing), for deciding on individual school careers (predictive analytics), or for analysing imaging procedures in medicine. This raises ethical questions about the extent to which artificial intelligence should intervene in immediate life contexts and what is just, fair, responsible, and accountable. Finally, the constant progress in AI development provokes the question of the fundamental (future) relationship between humans and machines.
Although media didactics (learning with AI) and media education issues (learning about AI) can be analytically separated, these considerations show that they are interwoven in many respects and partly mutually dependent. For concrete media education work in school and extracurricular contexts, the question arises as to whether and in what way artificial intelligence influences our understanding of media literacy.

A new understanding of media literacy

ARTIFICIAL INTELLIGENCE AND MEDIA LITERACY

The term media literacy refers to the individual knowledge, skills, and abilities required to meet the demands and challenges of an increasingly mediatised and digitalised world (Herzig, 2020b). Although the emphasis varies, many approaches to media literacy share the goal of enabling cultural, political, and social participation in the sense of an individually and socially empowered subject.
In Germany, the specific sub-competences to be acquired have been differentiated by all federal states in so-called "competence frameworks". If we take the competence framework for media education at Bavarian schools (mebis, 2019) as an example, the following AI-specific competencies would need to be concretised or supplemented (and adapted to specific school levels) against the background of previous considerations:

1. Basic skills
   - Know and understand the basic characteristics and properties as well as methods of artificial intelligence (e.g., weak and strong AI, symbolic and neural AI, machine learning and neural networks, deep learning)
   - Understand the basic properties, function, and training of language models (e.g., transformer architecture, tokenisation, vectorisation, parameters, training process, training data)
2. Searching and processing
   - Have a basic understanding of the special features of AI-based search engines and use them in a reflected manner (e.g., role of semantics and context, personalisation, natural language processing)
3. Communicating and cooperating
   - Design human-machine dialogues with generative AI in a goal-oriented manner and use them for personal learning processes and skills development, as well as for collaboration with others (e.g., prompt engineering, feedback, dialogue control)
4. Producing and presenting
   - Reflectively use tools for automated text/image/sound production in the context of personal (creative) designs
   - Know and observe legal and ethical framework conditions when using (generative) AI (e.g., data protection, discrimination)
5. Analysing and reflecting
   - Analyse, compare, and critically evaluate AI-generated information (e.g., fact-checking, biases, disinformation, hallucinations)
   - Assess forms of artificial intelligence in relation to human thought and behaviour (e.g., creativity, intuition and emotion, human image)
   - Recognise and assess the influence of (generative) AI on values, role models, world views, everyday, professional and work processes, and social, political, and economic practices

Fostering sensitivity by experimenting with AI-generated images

Ill. 2: Media literacy at secondary level I: knowing how an algorithm learns with input data is the starting point for understanding more extensive training processes[2]

EXAMPLES OF MEDIA PEDAGOGICAL REALISATION

Primary school

Initial engagement with AI can already be initiated at primary school level. A basic understanding and corresponding awareness of AI-based image design can be developed within the competence area of "producing and presenting". To this end, children can first be encouraged to describe how they recognise certain objects in images. This demonstrates how easily humans can recognise complex objects in their entirety, such as an animal species. Describing what we see – e.g., as a painting instruction for someone else – is much more challenging. Starting with simple geometric shapes and objects, learners can create such descriptions by identifying recurring structures, shapes, and patterns. These can then be applied to more complex images, such as a cat's face, where circular or triangular shapes and different colour shading and textures in the fur play a role. If a computer is to recognise such objects, it becomes clear that it needs a large number of examples to do so, e.g., to identify the shape and arrangement of a cat's eyes, ears, and nose, because these features vary slightly for every cat (Ill. 1). When a computer learns, it identifies recurring patterns and structures in the learning material – the data – and needs numerous examples to provide reliable results. In a second step, the children can create their own images in a data-safe environment with the help of an image-generating AI by formulating appropriate prompts and observing how well the AI can generate such images. They can also examine how to recognise that the images are not original photographs of objects.

Sensitivity to artificially generated images can also be encouraged through experiments with the AI by having learners generate unrealistic images, such as a cat with green fur or with the ears of another animal. This highlights that images can be deliberately manipulated and that specific information and knowledge about the respective objects and contexts is required to identify this. These activities also address aspects of the competence area "analysing and reflecting".

Becoming familiar with machine learning and neural networks

Secondary level I

In secondary level I, it is advisable for students to expand their basic understanding and become more familiar with machine learning and the basic workings of neural networks (Ill. 2). To do this, they can use a simple artificial neuron (perceptron) to understand how it learns, for example, to only switch on the lights in a factory hall when it is night and when people are working in the hall. With traditional algorithms, this problem can easily be solved with the rule that the light is switched on when the above conditions are met. For the artificial neuron, the learners would define 2 inputs for the time of day and the working status (day = 1/night = 0 and work = 1/break = 0). For the 4 possible combinations of inputs, the output light = 1 should only be produced if the above conditions are met. The output of the perceptron is calculated using the sum of the products of weight and input. With random values for the weights and a threshold value, the students start the calculation for all 4 possible input combinations, where, for example, the time of day and the work status could be weighted as equally important. If the threshold value is exceeded, the output is 1, i.e., the light is switched on. If an output is not correct, the weights are adjusted until the output is correct in all cases. Such a procedure illustrates in a simplified way how an algorithm learns with input data and serves as the starting point for understanding more extensive training processes. For example, if dogs and cats are to be recognised in images, the steps of processing the input, determining the output, comparing it with the correct result and, if necessary, adjusting the weights (and possibly the threshold values) are also run through. This example shows how the complexity of such processes increases, requiring more complex networks with different layers in which individual sub-patterns are recognised and learned. Learners also come to understand that the trained network does not contain an explicit solution rule, but rather a specific combination of weights and threshold values, which are not meaningful as such. The rule lies in the training and learning process of the network. At the same time, students learn that input data for a neural network must be available in machine-readable form, i.e., numerical form. For images, this might involve the colour value of a pixel, while for words it is essential to encode them in a way that also conveys semantic information where possible. This is achieved, for example, by using vectors with similar values for similar words.

Such an exploration of the basics of AI – as briefly outlined here – can foster an understanding for the further examination of how AI training data plays a significant role and that a language model does not rely on a knowledge base. In the absence of training data for a given content area, it may also produce false or invented results.

AI has transformed human forms of action and expression

CONCLUSION

With intelligent tutorial systems and machine learning methods, artificial intelligence offers automated possibilities for recognising patterns and correlations, creating forecasts, making personalised recommendations, supporting decision-making processes, and independently generating and analysing text, image and sound documents. This has considerably transformed human forms of action and expression. At the same time, the results of such processes are not (or no longer) traceable in their origin, rely on stochastic processes and non-transparent training data, but are generally highly plausible and often indistinguishable from human-created products.

Need for a basic understanding of the technological foundations of AI

This underscores the need for media education to foster a basic understanding of the technological foundations of AI in the future – in comparison to dealing with previous media – because this is the only way to recognise and understand the opportunities and problems arising from AI. Additionally, a greater focus on the design of human-machine communication will be essential to leverage the potential of (generative) AI for learning and the everyday world. While the operational handling of AI tools, especially chatbots, may seem simple, it demands advanced skills in terms of recognising the user's own information needs, translating them into target-oriented prompts, analysing and evaluating the outputs and, if necessary, designing follow-up communication. Such competences are also tied to basic skills in self-regulating learning processes and expertise in the respective application context. ■

NOTES

[1] *The image was generated with* Bing *with the following prompt: "Create an authentic photography of a teacher in a classroom with diverse pupils (girls, boys, POC, Caucasian). The whiteboard shows a picture with a cat that was created by AI. We see the pupils from the back with the same cat on their computer screens."*

[2] *The image was generated with* Bing *with the following prompt: "Create a photography of a group of four pupils (diverse, age 14-17) sitting in front of a computer in the classroom analysing algorithms."*

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