Chapter 4
AI Transformation for Learning in Organizations

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ABSTRACT

In this chapter the authors examine how AI applications support specific learning and training strategies in organizations, empowering individuals to develop their skills, allowing organizations to make data-driven decisions, and ensuring that learning is an ongoing and engaging process. Research shows that AI is an excellent instrument for learning in organizations as it aids in the preparation of instructional materials and helps learners progress in many different ways. So, there seems to be a need for a specific approach to AI pedagogy, which focuses not only on what AI can do but also on which learning activities and learning objectives can be supported by AI applications. As AI technology continues to advance, it will play an even more significant role in shaping the future of learning and development in the organizations, but this should always follow a humanistic perspective and a critical approach.

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1. INTRODUCTION

The purpose of this chapter is to analyze and discuss AI transformation in terms of pedagogical and technological applications for learning, and to answer the overall question: how do AI applications support specific learning and training strategies in organizations?

Learning organizations are dynamic entities that prioritize continuous learning, adaptation, and growth as part of their core values. While the concept of a learning organization is immensely beneficial, it is not without its challenges. But there are several obstacles that organizations face when striving to become learning organizations. For example: resistance to change, learning overload, individuals' engagement, insufficient and inadequate learning infrastructures, cultural resistance, among others.

Despite these challenges, the pursuit of becoming a learning organization remains essential in today's fast-paced, knowledge-driven world. Overcoming these obstacles demands patience, perseverance, and a commitment to fostering a culture of learning and improvement at all levels of the organization. In the end, the benefits of a learning organization, such as increased innovation, improved problem-solving, and enhanced adaptability, make the journey worthwhile.

In today's rapidly evolving world, staying competitive and adaptable is paramount, and AI plays a pivotal role in achieving this. AI is widening the possibilities for the way organizations approach learning as an ongoing, engaging process. As AI technology continues to advance, it will play an even more significant role in shaping the future of learning in organizations.

Namely, there seems to be a need for a specific approach to AI pedagogy, which focuses not only on what AI can do but also on which learning activities and learning objectives can be supported by AI applications. We are now beginning to understand the potential, as well as the social and ethical implications of AI. Nonetheless, what is clear is that the topic of AI in learning is too important to be left to engineers and entrepreneurs. Instead, it is critical that educators, learning scientists, and other stakeholders engage, to ensure that the AI applied in educational contexts best supports the learners and the learning (Zawacki-Richter et al., 2019).

Firstly, we have to understand what Artificial Intelligence (AI) is today, explaining how AI seeks to simulate human intelligence processes through machines, enabling them to learn, reason, make decisions, and solve problems. The concept of Machine Learning is crucial, as it is one of the main areas of AI that focuses on creating algorithms and models capable of learning from data and improving their performance over time without requiring any additional programming. Another significant aspect is the connection with Artificial Neural Networks, which are models inspired by the structure and functioning of the human brain, and are essential in many AI applications today, such as computer vision, natural language processing, and games. Natural Language Processing (NLP) is a subfield of AI that focuses on the interaction between computers and humans through human language, allowing machines to understand, interpret, and generate text. Additionally, another subfield of AI that involves algorithm development is Computer Vision, which employs techniques to enable machines to "see" and interpret images and videos, enabling applications such as object recognition and pattern detection.

The potential of Artificial Intelligence took a long time to be fully explored. Many recent advancements have yet to reach widespread use. However, AI-driven systems are increasingly being implemented in schools, colleges, and universities, as well as in training programs. While many people fear that AI in education means the replacement of teachers by robots, the reality is less dramatic. The connection between AI and Education is also more complex than is generally assumed. A commonly used approach involves learning with AI, learning about AI, and preparing for AI (Holmes et al., 2019). Learning with AI (often referred to as "Artificial Intelligence in Education" or "Learning with AI") involves learner-centered applications (such as intelligent tutoring systems, dialogue-based tutoring systems, exploratory learning environments, automated text assessment, and conversational agents); institution-focused AI (for recruitment, scheduling, and other administrative applications); and, in more theoretical terms, AI focused on the teacher (although there currently seem to be few examples of this type). The connection between AI and education also entails learning about AI (how it works) and how to prepare for AI (the impact of AI on humans, raising ethical, bias, fairness, and manipulation questions).

Educational robotics has long been developed as a tool for learning, with applications in science, technology, mathematics, computer science, and other school subjects in recent years. Similarly, AI has been applied in domains such as physics, mathematics, programming, and reading. Typical examples often include intelligent tutoring, knowledge representation, autonomous agents, and natural language processing. AI in education has also been used to enhance the efficiency of teaching and optimize resources. Some examples include iTalk2Learn, Third Space Learning, Duolingo, Thinkster Math, and EdTech Foundry. In many cases, AI in education has significantly improved students' learning environments and classroom interaction at universities. In recent times, differentiated and individualized learning has become the focus, and teachers' workloads have been reduced with the support of AI technologies like ChatGPT. This is a rapidly evolving field that requires ongoing updates by educators, students, and learning organizations.

It is also essential to have an understanding of Ethics and Responsibility in AI, particularly in the research and application of AI that can have consequences in terms of privacy, security, and social impact. There are many ethical issues related to the application of Artificial Intelligence (AI) for learning. First and foremost is privacy and data protection, which concerns the collection and storage of data for personalized learning purposes. It is essential to ensure that data is protected from unauthorized access and that learners have control over their personal information and data.

On the other hand, AI algorithms are influenced by the data collected during their training, which can result in discriminatory or unfair decisions. Similarly, the implementation of AI technologies can exacerbate inequalities if they are not accessible to all the learners, especially those with limited resources. It is crucial to ensure that AI does not increase digital exclusion and that everyone can access learning opportunities.

Also, the opacity of AI algorithms can generate distrust and make it difficult to understand decision-making processes. AI systems for organizations must be transparent and capable of explaining their recommendations understandably for all the stakeholders. Who is responsible when an AI recommendation leads to a negative outcome? It is essential to establish clear accountability for AI systems and ensure that they are designed to make ethical decisions. The main factor here is perhaps "trust in AI" (Gillespie et al., 2023), but also important are access to AI by citizens and the (ethical) integration with normal human life.

2. THE GLOBAL AI TRANSFORMATION

The extensive survey by Zawacki-Richter et al. (2019) provides a useful context for AI in Education and Training. According to the authors, the birth of AI dates back to the 1950s when John McCarthy organized a two-month workshop at Dartmouth College in the United States. In the workshop proposal, McCarthy used the term "artificial intelligence" for the first time in 1956 (Russell & Norvig, 2010, p. 17): "The study [of artificial intelligence] should proceed on the basis of the conjecture that every aspect of learning or any other feature of intelligence can in principle be so precisely described that a machine can be made to simulate it. An attempt will be made to find out how to make machines use language, form abstractions and concepts, solve problems now reserved for humans, and improve themselves."

A comprehensive definition of AI was provided by Baker and Smith (2019): "Computers performing cognitive tasks, usually associated with the human mind, especially learning and problem-solving" (p. 10). These authors explain that AI does not refer to a single technology but is a comprehensive term describing various technologies and methods such as machine learning, natural language processing, data analysis, neural networks, or generative algorithms. Nonetheless, machine learning is crucial as a process of AI systems for supervised and unsupervised classification and sampling, for example, predicting the probability of a student dropping out of a course or being admitted to a program, or identifying topics in written works. Popenici and Kerr (2017) define machine learning "as a subfield of artificial intelligence that includes software capable of recognizing patterns, making predictions, and applying newly discovered models to situations that were not included or addressed in its initial design" (p. 2).

Artificial Intelligence (AI) has already significantly altered organizations, societies, and individuals. In many cases, it can exhibit substantial analytical capacity based on large volumes of data and a learning process that enables it to predict changes in its external environment. During AI's formative years, the focus of algorithms was generally limited to supervised and unsupervised learning, inspired by biological organisms and the physical properties of nature, and then computationally establishing a response to solve problems within a data universe (Kar, 2016). However, traditional AI algorithms require structured data both for model construction and information processing. These older, established AI algorithms, such as neural networks, generative algorithms, decision trees, random forests, support vector machines, k-means clustering, and many others (Duan et al., 2019), were severely limited in their capabilities due to these constraints.

Recent AI algorithms, which have evolved over time, have become capable of processing data more naturally, making it possible to extract unstructured data such as raw text and images. AI algorithms designated as "deep learning" and "reinforcement learning" have evolved into specific algorithms such as convolutional neural networks and recurrent neural networks, gaining prominence for their ability to analyze images, audio, and even video (LeCun et al., 2015). Furthermore, industrial needs involving text extraction and Natural Language Processing (NLP) have multiplied, leading to the development and growth of algorithms that can work with unstructured data. Algorithms like Bidirectional Encoder Representations from Transformers (BERT), Long Short-Term Memory (LSTM), and language models have gained prominence in recent applications (Guan et al., 2019, Kushwaha and Kar, 2021).

Many of these algorithms heavily depended on two resources: (1) large volumes of data to train and operate the algorithms and (2) highly complex computational resources to deploy and run the algorithms. However, real-world applications did not always have access to high-level computational resources. Over time, new AI models were developed and adopted, such as federated learning and "tiny" machine learning algorithms, for industrial applications (Li et al., 2020a, Li et al., 2020b). Many of these applications worked in scenarios where data was not initially available to train these algorithms, a problem referred to as the "cold start problem." If data wasn't available, how could these applications learn patterns and predict future trends? These limitations led to the development of reinforcement learning algorithms that gained prominence in both marketing and financial management applications (Singh et al., 2022a, Singh et al., 2022b).

Current news from around the world make us aware that AI is not as sophisticated as many argue. For example, that "AI is better than humans at image recognition". Several experiments show the opposite (https://neurosciencenews.com/ai-image-recognition-21513/). Another is that "AI doesn't need people". But again, this is not true. There are AI companies based in developing countries (https://time.com/6247678/openai-chatgpt-kenya-workers/) where workers spend their entire day online identifying and labeling objects ("here is a person", "here is a car", "here is another person"). But humans are also needed to design the neural network and write the algorithms that train that network.

In parallel with the continuous development of AI algorithms, there has been an increase in the number of studies related to chatbots in the literature (Lokman and Ameedeen, 2018). These chatbots typically use natural language processing (NLP) to respond to user queries, transferring them to the best sets of available responses in the system. To provide real-time feedback, chatbots adopted language models along with deep learning to handle NLP challenges (Bellegarda, 2004, Melis et al., 2017, Kushwaha and Kar, 2021). The recent launch of OpenAI's ChatGPT demonstrates a significant expansion of chatbot capabilities through the integration of deep learning and language models based on the Generative Pre-training Transformer (GPT) architecture (Radford et al., 2018). Language models attempt to predict the probability of a word sequence typical of a human interaction and present the most likely response through generative and discriminative algorithms, often applying deep learning and transformer-based neural network architectures (Bengio et al., 2000, Bellegarda, 2004, Vaswani et al., 2017). ChatGPT uses a combination of unsupervised pre-training and supervised fine-tuning to generate responses similar to those of humans and provide information on topics that appear to be from a human expert. It is a language model based on billions of parameters, trained on a diverse set of naturally sourced data from various internet sources such as web pages, books, research articles, and social media conversations. While current language models generally employ deep learning subjected to supervised learning, future evolutionary models may be built based on reinforcement learning (Uc-Cetina et al., 2022).

The recent global and widespread transformation imposed by ChatGPT has demonstrated a tremendous variety of use cases for this technology in organizations, including software development and testing, poetry, essays, business letters, and contracts (Metz, 2022, Reed, 2022, Tung, 2023). However, it has also raised a series of concerns related to the difficulty of distinguishing human authorship from AI authorship within academic communities, reigniting the debate about more traditional human activities (Else, 2023, Stokel-Walker, 2023). These challenges arise because ChatGPT, and others such as Bard and Claude, may result in both positive and negative impacts on the society in which we live, so there must be some precaution in the application and use of the technology.

3. PEDAGOGY AND AI TOOLS

In the context of academic learning there are two main issues to be resolved: (1) Current AI tools, like other digital technologies, are primarily viewed and used instrumentally, obscuring its fundamental role as a constitutive factor of human perception and experience (Hillman & Säljö, 2016; Malafouris, 2013; Säljö, 2019), and (2) predominant pedagogical approaches denote a uniformizing character, usually centered on the instructor, implying a limited view of instruction that disregards other types of learning situated outside these restrictive boundaries (Pargman, 2019; Selwyn et al., 2020).

These issues make it essential to understand and legitimize other "spaces of possibility" (Selwyn, 2020). As a way to contribute to the improvement of learning processes, Hatch et al. (2021) highlight the importance of breaking down barriers between learning "inside" and "outside" of the institution, allowing students to pursue their interests. Gee (2018) argues that the most powerful learning experiences for young people have been found in experiences and environments outside the traditional school system, developing practices rarely used in traditional schools.

Considering the typical characteristics of AI that may be applied to the specific domains of education and training, there are many ways to approach the selection and use of the tools for successful learning experiences. In a recent report, Baker and Smith (2019) address educational AI tools from three different perspectives: a) student-centered, b) teacher-centered, and c) system-centered. Tools aimed at students are software applications that students use to learn a subject, such as adaptive learning management systems or personalized Intelligent Tutoring Systems (ITS). Teacher-centered systems are used to support the teacher and reduce their workload by automating tasks such as administration, assessment, feedback, and plagiarism detection. These tools can also provide information on students' learning progress so that the teacher can proactively guide them. System-centered tools are those that provide information for administrators and institutional-level managers, such as monitoring student dropout patterns. The same approach would apply to the context of organizational training of human resources.

Intelligent Tutoring Systems (ITS) can be used for teaching. Based on learning models, generative algorithms, and neural networks, ITS can make decisions about a student's learning path, identify the content to be selected, provide cognitive support, and promote dialogue with the student. ITS has enormous potential, especially in large-scale organizations and distance education institutions that offer training and courses to thousands of learners, a situation where individual tutoring is impossible. Research shows that learning is a social exercise; interaction and collaboration are at the heart of the learning process (Jonassen, Davidson, Collins, Campbell, and Haag, 1995).

However, online collaboration needs to be facilitated and moderated (Salmon, 2000). AI in education can contribute to collaborative learning by supporting group-adapted teaching based on recognized learning models, facilitating online group interaction, or summarizing discussions that can be used by a human tutor to guide learners. Finally, also leveraging ITS, Intelligent Virtual Reality (IVR) may be used to engage and guide learners in authentic virtual reality-based learning environments and games. Virtual agents can act as tutors, facilitators, or peers, for example, in virtual or remote labs (Perez et al., 2017).

With the advancement of AI in education (AIEd) and the availability of large volumes of student data, it becomes possible to analyze learning processes. Luckin et al. (2017) recognize a "renaissance in assessment" (p. 35). They believe that AI can provide real-time feedback and assessment. Instead of stopping teaching to assess students, AIEd can be incorporated into learning activities for continuous analysis of student performance. Algorithms have been used to predict the probability of a student failing a task or dropping out of a course with a high level of accuracy (e.g., Bahadır, 2016).

The recent emergence of Chatbot systems known as Large Language Models (LLMs), such as ChatGPT, Bard and Claude, brings a more practical and real perspective on AI usage. For example, incorporating ChatGPT into higher education teaching practices can significantly enhance the learning experience for both students and teachers. By generating educational materials, creating discussion topics, providing personalized feedback, and supporting active and collaborative learning, ChatGPT empowers teachers to interact with students more effectively and provide a deeper understanding of subjects. In this regard, as AI technologies continue to evolve, educators must stay informed and adapt their teaching methods to make the most of these powerful tools. However, like all tools, there are also disadvantages, such as:

- ChatGPT's knowledge base (version 3.5) only extends up to September 2021, which means it may not have the most up-to-date information on certain topics;
- Since ChatGPT is trained on internet data, it can inadvertently reproduce biases and distortions existing in the data used for its training, requiring the users to be aware of the issue and always verify the information;
- While ChatGPT can generate human-like responses, it may occasionally produce factually incorrect or inappropriate content, requiring supervision and discernment by human instructors;
- ChatGPT lacks emotional intelligence or empathy, which can be a limitation when discussing sensitive topics or providing emotional support to learners.

4. PEDAGOGICAL STRATEGIES

Pedagogical strategies are also relevant, and AI tools should be aligned with them, as previously mentioned (Holmes et al., 2019). The UNESCO publication "Understanding AI and Education" (2021) clearly illustrates the educational potential of AI through various application scenarios. The topics and examples presented are adapted from this source.

4.1 Intelligent Tutoring Systems (ITS)

Of all the educational applications of AI, ITS have been researched the longest (over 40 years). They are the most common AI applications in education and have been tested by more students than any other. Additionally, ITS have attracted the highest level of investment and interest from major technology companies worldwide and have already been adopted by organizations worldwide.

In general, ITS work through step-by-step tutorials that can be customized for each student or trainee, covering topics in structured disciplines like accounting, mathematics or physics. The system determines an optimized learning path through learning materials and activities, using subject matter expertise to respond to student questions and performance. This approach can also be implemented in learning management systems such as Moodle and Open edX or platforms like Khan Academy.

As users progress through learning activities, the system relies on operation records and machine learning to automatically adjust the difficulty level and provide hints or guidance based on the student's strengths and weaknesses, ensuring efficient topic learning. Some ITS also capture and analyze data on the student's emotional state, including monitoring their gaze to determine the level of attention.

However, while it may seem like an interesting model, it's important to recognize that the pedagogical assumptions embedded in ITS and their typical knowledge transmission approach ignore other possibilities valued by the Education Sciences, such as collaborative learning, exploratory learning, and productive failure, for example. In particular, the "personalized learning" provided by ITS merely selects paths within the programmed content, rather than promoting the student's problem-solving abilities.

4.2 Dialogue-Based Tutoring Systems

Dialogue-based tutoring systems (DBTS) use natural language processing and other AI techniques to simulate a dialogue between a human tutor and the student as they progress through their online tasks. Initially more common in the field of Computer Science, DBTS have more recently appeared in other less structured domains. DBTS take a Socratic tutoring approach, using AI-generated questions instead of guidance instructions, allowing for a conversation where students can discover appropriate solutions to problems on their own. The goal is to encourage students to develop knowledge for a deep understanding of the topic, rather than the superficial understanding that may result from some ITS. Currently, there are relatively few DBTS in use. The most widely tested one is AutoTutor (Graesser et al., 2001). Watson Tutor is a well-known commercial system developed by IBM and Pearson Education.

4.3 Exploratory Learning Environments

An alternative to the step-by-step approaches of ITS and DBTS is provided by Exploratory Learning Environments (ELEs). These adopt a constructivist philosophy: instead of following a step-by-step sequence, as in the "knowledge transmission" model favored by ITS, students are actively encouraged to construct their knowledge by exploring the learning environment and making connections with the existing knowledge. The role of AI in ELEs is to minimize the cognitive overload often associated with exploratory learning by providing automated guidance and feedback based on collected data and machine learning. This feedback includes error recognition and proposes alternative approaches to support the learners as they explore the solutions. In reality. Examples include 'ECHOES' (Bernardini et al., 2014), 'Fractions Lab' (Rummel et al., 2016), and 'Betty's Brain' (Leelawong and Biswas, 2008).

4.4 Automatic Text Assessment

Instead of just promoting academic work on computers through adaptive support, Automatic Text Assessment (ATA) uses natural language processing and other AI techniques to provide automatic feedback on writing. Typically, there are two overlapping approaches to ATA: formative ATA, which allows the learners to improve their writing before submission, and summative ATA to facilitate automatic grading of writing afterward.

In practice, most ATAs focus on grading rather than feedback; they were primarily designed to reduce assessment costs and can be considered components of instructional management. However, since its introduction, summative ATA has been controversial. For example, it has been criticized for giving credit to students for superficial features like sentence length, even if the text doesn't make sense. These systems are also unable to assess creativity. Summative ATA also does not address academic tasks that may involve easily accessible "deep-fake" essays - essays written by AI technologies. These essays are likely challenging to detect, even for Turnitin. Finally, using AI to assess tasks also doesn't recognize the value of assessment. While assessment can be time-consuming and tedious, it can also be the best opportunity for the instructor to understand the learner's skills.

4.5 Language Learning and Reading through AI

Language learning and reading tools increasingly use AI in their approach. For example, some use personalized learning paths in the style of ITS, leveraging AI-enabled voice recognition. Typically, voice recognition is used to compare student production with recordings of native speakers to provide automatic feedback that helps the learner improve pronunciation. Other uses of machine translation include helping students read learning materials in other languages and enabling learners from different cultures to interact more easily with each other. Some systems automatically detect and analyze reading skills to provide individualized feedback to students. AI applications for language learning and reading include AI Teacher, Amazing English, Babbel, and Duolingo.

4.6 Intelligent Robots

The use of AI-integrated robots, often referred to as "intelligent" robots, is also used in education, especially in educational environments for children with learning difficulties or disabilities. For example, humanoid robots with speech capability have been used with students with special needs on the autism spectrum, providing predictable mechanical interactions instead of human interactions, which can be confusing for these students. The goal is to develop communication and social interaction skills. Another example is telepresence robots for students who cannot attend school due to illness, humanitarian crises, or other reasons, allowing them to access a classroom. A third example is the use of humanoid robots like Nao or Pepper in kindergarten classes in Singapore to teach young children programming languages and other STEM disciplines.

4.7 Learning Agents

It's possible to learn a topic more deeply and with better retention by teaching it to others, a learning method known for a long time. This effect has been explored by various AI approaches. For example, in "Betty's Brain" students are encouraged to teach a virtual student named Betty about a river ecosystem. In another example, from a Swedish research project, students teach a virtual agent the rules of a mathematics-based educational game. A third example, from Switzerland, involves young children teaching handwriting to a humanoid robot, an approach that has been shown to stimulate metacognition, empathy, and self-esteem.

4.8 VR and AR Applications

Virtual Reality (VR) and Augmented Reality (AR) are two related innovations that have been applied in educational contexts and are often combined with machine learning and other AI techniques to enhance the user experience. VR has been used in teaching various subjects, from elementary education to astronomy, biology, geology, and industry. VR headsets provide an immersive experience that excludes the physical world, allowing users to feel like they've been transported to other real-world environments or imagined worlds (such as the surface of Mars, the interior of a volcano, or a human uterus with a developing fetus). Some VR innovations use AI techniques to control realistic avatars, enable voice control through natural language processing, or generate complete environments from a few initial images.

On the other hand, AR overlays computer-generated images onto the user's real-world view (like a fighter pilot's visor). When a smartphone camera is pointed at a specific QR code, a 3D human heart in AR can be revealed, allowing for detailed exploration. AR can also include image recognition and tracking through AI processes. This is the technology that enables some apps like Instagram or Snapchat to add bunny ears or cat whiskers to people's images.

4.9 Learning Network Organizers

Learning Network Organizers (LNOs) are AI tools that allow networked learners and instructors to organize learning activities. LNOs typically match participants based on their availability and areas of expertise to facilitate coordination and cooperation. An example is "Third Space Learning," which connects UK students at risk of failing in math with math tutors from other countries. Another example is the "Smart Learning Partner," which involves an AI-driven platform that allows students to choose and connect with a human tutor via mobile, similar to a dating app, to receive personalized support.

4.10 Collaborative Learning through AI

Collaborative learning, in which students work together to solve problems, is known to improve learning outcomes. However, effective collaboration among learners can be challenging to achieve. In this regard, AI can transform collaborative learning in several ways: a tool can help connect remote learners; it can identify the most suitable people for specific collaborative tasks and group them appropriately; or it can actively contribute to group discussions as a virtual agent. Although specific examples have not been identified, this is currently an area of interest.

4.11 Instructors and AI

Despite the potential to empower instructors, the use of AI tools to improve teaching processes has so far received much less attention than AI systems for students. Currently, researchers and computer scientists tend to think about developing applications for instructors to use at the end of the process, such as dashboards to display student data. However, this is likely to change. Many AI applications for instructors can help reduce workload by automating tasks such as assessment, plagiarism detection, administration, and feedback. It is often argued that this could free up time for teachers to invest in other tasks, such as providing more effective individual support to students. While this may have some benefits in contexts where instructors are scarce, the goal of eliminating the need for human teachers reveals a fundamental misunderstanding of their essential social role in the learning process.

5. TOWARDS A STRATEGY FOR AI IN LEARNING ORGANIZATIONS

As previously mentioned, any emerging technology, especially applications involving AI, can raise new ethical and legal questions, such as those related to social responsibility or decision-making. The ethics of artificial intelligence has received significant attention from researchers (e.g., Boddington, 2017; Floridi, 2019; Jobin et al., 2019; Whittaker et al., 2018; Winfield and Jirotka, 2018) both in Europe and around the world (e.g., the European Union, 2019; the UK House of Lords, 2018; UNESCO, 2019; and the World Economic Forum, 2019), with numerous other initiatives on AI ethics emerging in recent years (e.g., the Ada Lovelace Institute, 2019; AI Ethics Initiative, 2017; AI Now Institute, 2017; DeepMind Ethics & Society, 2017; Future of Life Institute, 2013).

All these efforts primarily focus on the collected data (involving issues like informed consent, data privacy, and data collection biases) as well as how this data is analyzed (involving issues like bias, transparency, and statistical apophenia - for example, finding patterns where there are no significant patterns). The Montreal Declaration for the Responsible Development of Artificial Intelligence (2018), for instance, offers a comprehensive approach involving ten principles centered around human well-being, respect for autonomy, privacy protection, solidarity, democratic participation, fairness, diversity, prudence, responsibility, and sustainable development. Currently, no such statement exists specifically for the ethical issues raised by AI in education (IAED).

The ethics of pedagogy, including the choice of the pedagogical model were discussed by Shiohira & Holmes (2023); almost all commercial AI-based learning tools adopt an effective behaviorist or instructivist pedagogy. This approach to teaching and learning prioritizes memorization over critical thinking. AI systems can also take power away from teachers, often turning them into mere "facilitators", i.e., those who connect the equipment and maintain classroom behavior. But human instructors do much more than that.

The ethics of educational data and learning analytics has been the subject of research (e.g., Ferguson et al., 2016; Slade and Prinsloo, 2013; Potgieter, 2020), covering a wide range of topics that cannot be fully summarized here. But several aspects can be considered, first: "the ethical and privacy aspects of learning analytics are varied and change as data use reveals information that was previously inaccessible" (Ferguson et al., 2016, p. 5). Second, the ethics of learning analytics involves various types of issues, including but not limited to informed consent and privacy, data interpretation, data management, and perspectives on data (e.g., institutional vs. individual); it can also include much broader issues like power relations, surveillance, and the purpose of education (Slade and Prinsloo, 2013). Third, it has been argued that "educational data mining is not the superconductor of truth that some of its advocates believe... and the transformative impact it will have on students' autonomy is a cause for concern" (Potgieter 2020, pp. 3, 6).

Some research has also focused on ethical issues in related areas such as user data modeling, e-learning environments, and intelligent agents. For example, in user data modeling, there are concerns about the security and privacy of this data (e.g., Schreck, 2003), the possibility of inspection (e.g., Zapata-Rivera and Greer, 2004), and individual privacy (e.g., Kobsa, 2007). More recently, dedicated workshops have been held at prominent conferences (e.g., FairUMAP, in Mobasher et al., 2020), with significant contributions exploring issues like fairness (Sacharidis et al., 2020), transparency (Schelenz et al., 2020), and bias (Deshpande et al., 2020). Researchers in the e-learning domain are also concerned with the ethical issues raised by the systems they build, including issues of fairness, diversity, surveillance, consent, identity, and confidentiality, as well as student privacy: "when an observer [which could be an automated system] monitors..." (Anwar and Greer, 2012, p. 63). However, it's notable that other e-learning researchers seem more interested in the ethical practices of students, such as copying and cheating in learning (e.g., Gearhart, 2012).

Finally, researchers and computer scientists developing intelligent agents like chatbots are also increasingly focused on the ethical issues raised by their work (e.g., Murtarelli et al., 2020; Richards and Dignum, 2019). More recently, the

World Economic Forum launched "RESET" - a framework and set of principles for governing the responsible use of conversational AI (WEF, 2020) - which, although focused on healthcare, has clear potential for application in the ethical issues of intelligent agents in education. The RESET principles focus on safety, beneficence, effectiveness, data protection, humanization, responsibility, transparency, fairness, explainability, integrity, and inclusivity.

Other important ethical concerns of AI in education revolve around computational approaches. How should data be analyzed, interpreted, shared, and used? Just like biases (conscious or unconscious) that can negatively impact students' civil rights, caution must be exercised regarding issues related to gender, age, race, social status, income inequality, and more. Finally, as the Facebook and Cambridge Analytica scandal demonstrated, data is always vulnerable to hackers and manipulation: "it is impossible to have privacy and personal control over large-scale data, so it is crucial that the uses to which data will be subjected are ethical - and that ethical guidelines are clearly understood" (Tarran, 2018, pp. 4–5).

However, the ethics of AI in education and training cannot be reduced solely to issues of data or computational approaches (Holmes et al., 2019). Research also needs to explicitly consider the ethics of instruction, which, although the subject of decades of research, is often overlooked. For example, research needs to explicitly address issues such as: (1) the purpose of learning (e.g., preparing students to pass exams or helping them fulfill their full potential), (2) the choice of pedagogy (mostly following a single theoretical approach, e.g. instructionalism or behaviorism, challenged by the educational sciences), (3) the role of technology in relation to teachers (replacing or complementing human functions), and (4) access to education (often seen through the ethical dimension of justice and equity). Furthermore, there is still limited research on what teachers and students expect from AI systems - such as requirements regarding student autonomy and privacy, on which teachers and students may not agree (Holstein et al., 2019). Looking at the corporate world, when organizations aim at behavioral changes, such as "leading" individuals to take a certain action, the entire sequence of pedagogical activities enhanced by AI needs to be ethically justified.

6. AI RESHAPING ROLES AND PROCESSES IN LEARNING ORGANIZATIONS

As previously mentioned, AI has emerged as a disruptive force in organizational learning, transforming the way individuals' access, engage with, and benefit from learning content. The multifaceted impact of AI on the learning process, encompassing both formal and informal educational settings, opens up to a world of opportunities and challenges posed by the integration of AI technologies into learning organizations.

One of these opportunities and/or challenge is related to the importance of tailored learning experiences and the AI's ability to create individualized learning paths for individuals thus increasing engagement and knowledge retention. The work of Baker & Siemens (2014) explores how data mining and learning analytics, often powered by AI, can be used to create personalized learning experiences for students. Their work provides valuable insights into the role of artificial intelligence in tailoring learning experiences to the needs of individual learners. They emphasize how AI can analyze data, adapt content, and provide real-time feedback to create more effective and engaging learning experiences.

Through advanced algorithms, AI systems can analyze an individual's learning history, preferences, and performance to recommend customized learning paths. This personalization ensures that individuals receive content and training that are directly relevant to their needs, thereby increasing engagement and knowledge retention.

On the other hand, AI tools have the potential to allow us to develop a more adaptive learning process, because learning systems can adjust the difficulty of content based on an individual's progress and performance (Siemens, 2005). These systems continuously assess an individual's performance and knowledge, adapting the learning materials to match their needs and obstacles. This dynamic approach ensures that individuals are neither overwhelmed nor under-challenged, promoting continuous growth.

But as Roschelle, J., Lester, J. & Fusco, J. (2020) highlighted, technology's impact on education (and learning) is often to amplify impacts, regardless of whether the impacts are intended. In order to be prepared for unintended impacts, it is crucial to rethink the role of human intelligence (the educators, leaders, decision makers and the learners) in the learning process with AI tools. Educators and trainers, for instance, need to adapt their teaching strategies to AI technologies, but they also should explore the transformative power of AI in learning as a way to revolutionize learning processes, making them more efficient, personalized, and impactful for both individuals and organizations.

There is a vast potential of AI in personalizing learning (Baker & Siemens, 2014), making education accessible (Holmes, Bialik & Fadel, 2023), improving skills assessment (Meyer, 2022), and facilitating data-driven decision-making (Siegel, 2013). As AI continues to evolve, the works of these authors provide a solid foundation for educators and organizational leaders looking to harness the transformative power of artificial intelligence in learning environments.

It is important for learners to understand that they also play a crucial role in the development and application of AI in several ways. Learners contribute to AI by generating data through their interactions with educational platforms, online courses, and digital learning materials. This data, including user behavior and performance data, is invaluable for training AI algorithms and improving the quality of AI-driven educational tools. Learners also provide insights into what works and what doesn't, learners can influence the ongoing development of AI systems in education. In this way they can collaborate with educators and content creators to design and develop AI-enhanced learning materials.

But it is very important to realize that as AI continues to shape the learning landscape, learners need to develop critical thinking skills and an understanding of AI's limitations, biases, and ethical considerations. This awareness empowers learners to be responsible users of AI technologies and informed contributors to discussions about AI in the learning process (Gašević, Siemens & Sadiq, 2023).

Learners are not passive recipients of AI in education; they are active participants and contributors. Their input, feedback, and engagement are essential for the responsible and effective integration of AI in educational settings. Moreover, learners who develop AI-related skills and awareness can also benefit from AI's capabilities in their lifelong learning journeys.

In this context, the relationship between pedagogy and AI must be one of collaboration and augmentation, hence AI has the potential to enhance and optimize pedagogical practices by offering new tools and capabilities that can benefit educators, instructors and learners. However, the effective and responsible use of AI in education requires careful consideration of ethical, privacy, and equity concerns. The ethical and societal challenges associated with AI adoption in learning needs careful consideration and regulation. The role of educators and policymakers in guiding the responsible integration of AI into learning environments will be crucial in harnessing the full potential of these transformative technologies.

7. CONCLUSION

In general, research shows that AI is an excellent instrument for learning in organizations as it aids in the preparation of instructional materials and helps learners progress in many different ways. So, for instruction and learning, AI is not a just a way of "cheating" as it provides the means to build summaries, show examples, create simulations and develop practice. It turns out that everyone must cultivate AI literacy to be able to perform on the job and be effective citizens in this world, but this should always follow a humanistic perspective and a critical approach.

The inappropriate use of AI for learning can affect the autonomy and the ability to make informed decisions. It is important to balance the use of AI with the need for critical thinking and learning success. For this purpose, we offer six recommendations:

Table 1. Recommendations

	Recommendations	Stakeholders
1	Emphasize the valued role of human instructors	Leaders, Instructors
2	Provide technical and pedagogical support to instructors	Leaders, Instructors
3	Associate AI tools with an accepted pedagogical model	Instructors, Students
4	Design and deliver instruction using ethical AI principles	Instructors, Students
5	Address issues of safety and privacy of AI use	Leaders, IT Staff
6	Notify users of specific guidelines and precautions	Leaders, IT Staff

In conclusion, the role of artificial intelligence in learning within organizations is transformative. It empowers individuals to develop their skills, allows organizations to make data-driven decisions, and ensures that learning is an ongoing, engaging process. As AI technology continues to advance, it will play an even more significant role in shaping the future of learning and development in the organizations.

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