Sezione monografica

Artificial Intelligence in Education
Intelligenza Artificiale ed educazione

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Collaborating with Machines. AI, Literacies, School[2]

1. AI Literacy: the centrality of prompting and the artificial conversation hypothesis

Thinking critically and developing awareness has always been one of the main goals of Media Education, indeed perhaps the main one. Thinking critically means using one's head and thus not letting oneself be influenced. Strong media effects theories (Wolf, 1992) and Frankfurt's critical theory (Horkheimer - Adorno, 1947) are certainly behind this goal.

To recognise that media effects are strong is to grasp an asymmetry of control and power between the media (and those who own them) and their recipients. Hypotheses such as that of the hypodermic needle (or the magic bullet) and subliminal communication give a good idea of what one wants to argue by alluding to at least two orders of considerations. The first. Media communication, the message it intends to convey (the bullet), always hits the target: in this sense it is magic, because it hits the target, it never misses. The second. Media communication behaves like a needle stuck under the skin: it inoculates behav-

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iors and values below the threshold of the viewer's consciousness, who has no way of noticing them (and in this sense the idea of subliminal communication represents the clearest materialization of this idea). There is here a first strong idea against which the promotion of critical thinking reacts: the idea that through the media a few, or at most only one, have the possibility of conditioning the choices of many. The idea of developing critical thinking is the antidote to the risk of the imposition of a single thought (Barbero, 2002; Freire, 1970).

Frankfurt's critical theory develops this theme and relates the spread of the media to the advent and development of mass culture. The latest stage in the evolution of the capitalist mode of production, the media apply the same methods to cultural production as are applied to the production of commodities. The result is that the cultural products become objects, are serialized and commodified. Here again, there are at least two considerations that can be made. The first is that cultural products are also sold and bought, just like other commodities. Culture also becomes a market, an economy develops around it. The second consideration is that if cultural products are mass-produced, they are the same for all their recipients and end up imposing fashions, trends, ways of thinking: standardization and massification are the consequence. Here we have a another idea, complementary to that one of single thinking: because of the media, the individual loses his originality, becomes homogenized, becomes the same as everyone else. The aim of developing critical thinking reacts, therefore, to the risk of uniformity, leveling, the cancellation of differences and divergence.

In Media Education research and work, the tool to defuse the risks of single thinking and massification has always been analysis. Given that the media are not transparent (Masterman, 1985; 1994), given that their messages are the result of a construction, in order to unearth the real intentions of those who govern them, it is necessary to disassemble them. It was precisely at this level that Media Education encountered semiotics and made it its working method, first at the semantic level (making analysis of the content of the message), then at the pragmatic level (making analysis of the communication strategies on which it is based), and finally at the socio-semiotic level, including in the analysis also the contexts and dispositions of the recipient in his or her relationship with the messages (Odin, 2011).

The prerequisite for the analysis of a message is twofold: it must be given in a materiality and it must have a textual form. As for materiality, it refers to a physical dimension, to an object endowed with permanence. This materiality is clearly visible in the media when they are technically reproducible: this is the case with cinema and audiovisuals which can be viewed repeatedly and which, thanks to the available technologies, can take advantage of the frame-stop and allow annotation in the form of semantic marking or tagging. The other aspect, textuality, refers to the fact that the message, materially available, must also be organized in textual form, i.e. in coherent parts held together by a communicative intentionality.

This works in the case of the film, the newspaper, the television series, the commercial, social media and web pages: but in the case of data and algorithms? In what sense can they be said to have a materiality and, above all, a textual form?

The answer comes from two levels of analysis, one of content, the other of structure.

As far as content is concerned, it is embodied in the products that are the result of the work of AI, as in the case of an image or a text (but also a piece of music, or a video) produced with generative systems, or in the trace of the interaction between such a system and human intelligence. In both these cases, we are dealing with a material component and a text: both an image and a piece of writing are equally so. At this first level, it seems that analysis can still work, since the object is materiality in textual form. The problem is that, by the admission of the computer scientists themselves, only an Artificial Intelligence could clearly discover that an image is a deep fake or that a text has been produced by a generative system. It would then be a matter of experimenting with new ways of working on textual forms that would make it possible to substitute the not always possible use of AI.

The structure, on the other hand, confronts us with realities - the data, the algorithms - that are not endowed with materiality and do not have a textual form, or at least do not have a visible textual form. Data, in fact, are in some way a textual object, otherwise they could not be 'read' if by an intelligent system; the same applies to algorithms, of which it is possible to provide a graphical representation. The problem is that all this concerns, as Flichy (1993) underlines, not the framework of use but the framework of operation: data and algorithms work 'behind' the interfaces and are therefore not visible within the framework of use that is offered to the users and through which they interact with the system in tactile or vocal form. At this second level, the assumption is that critical thinking can be exercised through conversation.

It is now clear, and the literature restores awareness of this, that prompting is a fundamentally important activity in the use of generative AI systems (Gregorcic - Pendrill, 2023). Syntactic correctness, low semantic ambiguity, and the pragmatic strategies to be used in the interaction are all decisive factors in obtaining effective responses and, particularly in the case of pragmatic strategies, in circumventing the blockages and/or reticence imposed on the system by the rules of behavior contained in the dataset on which it has been trained. In prompting, therefore, critical thinking is exercised at two levels.

At a first level, it makes aware the ability to elicit relevant answers, and the avoidance of producing ambiguity and provoking misunderstandings. The more precise and unambiguous the prompt, the better quality the AI response will be. A theme opens up here that deserves to be developed and that is the function of the culture of the human subject interacting with the AI. The breadth of cultural references (what Eco called the reader's reference encyclopedia) has always played an important role in text interpretation. If the text, in fact, is a lazy machine and only actualises its meanings through the reader's cooperation, the reader cooperates with it on the basis of what his cultural references allow him to do (Eco, 1979). The same principle of cooperation may (all the more) apply in the case of AI: without a broad reference encyclopedia, one is not able to detect AI's possible errors, but neither can one make it produce high-quality content in its responses.

The second level takes shape in the ability to converse with the AI in a strategic way. The dataset on which the AI is trained contains not only data, but also rules. These include ethical rules that 'teach' the AI what to do and what not to say. If one interacts non-strategically with the AI, one often cannot get around these rules: the AI responds by 'obeying' them. This makes it difficult to make it 'unbalance' and determine in this way, for example, whether it operates from bias. Here it is necessary for the human interlocutor to act strategically. This can be done by disguising one's questions, or by formulating them in an indirect manner: for instance, if one has asked Chat GPT for an opinion on such a singer and has been told that since it is an AI system it cannot formulate judgments, one can try asking it what judgment it would have if it were a music critic. At this second level, critical thinking becomes strategic and goes through the development of language skills. It would be interesting to recover the lesson of classical rhetoric and the reception of it by contemporary linguistics to try to decline it in the direction of persuasive and effective communication with AI.

The feeling is that a new chapter in the history of Media Literacy methods could be written in this direction: interaction psychology, linguistics and semiotics are certainly some of its constituent elements.

2. AI and Education: the reasons for interest and the problem of explainability

The topic of AI Literacy is certainly central within Artificial Intelligence and Education (AIED) research. It continues to represent a transdisciplinary space and project that is recognised as having the potential to promote transformation by facilitating the development of new paradigms for educational research. The specific reference is to different AI techniques applied to education, such as natural language processing (NLP), the development of artificial neural networks, deep and machine learning and genetic algorithms for the creation of intelligent learning environments. These techniques, used in education, have made it possible to detect different types of behavior to build prediction models as well as recommendation systems to support increasingly personalized learning processes (Chen - Xie – Hwang, 2020; Rowe, 2019). These aspects contribute to a more general reflection on how AI can become increasingly significant in educational contexts (school, university) by positioning itself as a research space and a tool for testing innovation. An open issue seems to be that of making teachers and students in particular understand how AI applications can be useful for the development of knowledge and skills, knowing that optimal use of AI technologies can produce better results.

Facilitating greater usability of AI in educational contexts presupposes a socially situated approach to technology, in which context assumes an increasingly relevant role in explaining AI-mediated processes (Ehsan *et al.*, 2021), anchoring the debate in the identification of perspectives that allow us to understand the characteristics of our time. Indeed, the aim should not be to substitute one technology for another, but rather to build communities capable of accommodating educational needs by seeking solutions through an alternative educational model of development, based on creativity, contextualisation and plural thinking (Panciroli, 2018).

This all goes back to the theme of explainability of algorithms (XAI), in which every explanation and meaning is conceived and designed within a soliciting educational environment, centered on social interactions between different actors, to give rise to confrontation and responsible participation. In schools a central role is given to teachers who, through the analysis of plausible case studies, identify problems related to teaching and anchor problem-solving to the use of AI techniques (§ 3). In the field of education, this process of explainability can be traced back to three main instances.

1) *Agentivity*. It concerns processes of co-designing and co-creating activities that contribute to constructing meaning about AI. In particular, explanations of AI should enable students, teachers and families to grasp the relationship with the aspects being analyzed, thus enabling them to make more informed decisions on whether or not to adopt AI (Facer - Selwyn, 2021). Specifically, student-teacher interactions can make transparent the methodological choices made or the stages of

the learning process through individual feedback given to students. The aim is to make it clear how AI can affect the overall structure of the process, creating the conditions for positive motivation to learn (Joshi - Radha - Churi, 2021).

2) *Literacy*. AI-based innovations bring out different ways of thinking about learning. This highlights the need to build an AI school curriculum (§ 4) recognising different levels of approach: a) the understanding of what AI is (literacy); b) the ability to learn with AI (knowledge); c) the ability to communicate and collaborate with AI in an increasingly integrated way (competence) (Long - Magerko, 2020).

3) *Accountability and trust*. The motivations behind the adoption of AI in education have not only a formative-didactic but also a socio-political value. In light of the possible potential of AI, UNESCO published the *Beijing Consensus* (UNESCO, 2019) in which the deployability of AI (XAI) is understood as a catalyst for education that can positively contribute to its improvement. In particular, it is highlighted that in XAI strategies it is important to consider to whom explanations are addressed, what the purposes are, and how to effectively communicate explanations to different stakeholders to support an informed and critical understanding of AI.

These three instances suggest some reflections on XAI from an educational perspective.

First of all, educational research must keep the pedagogical and computational aspects of AIED connected. While it is agreed that this change can occur through the use of advanced information technology, AI needs to be connected more to learning/teaching theories (Hwang *et al.,* 2020) (§§ 3 and 4).

Secondly, the different actors in the educational community (students, teachers, parents, educational agencies) can be considered both as actors in the innovation process and as its potential recipients. For instance, the deployability of AI is now a priority area of professional development for teachers as they play a design role by defining when and how to use intelligent systems to support learning in the classroom (Miao *et al.*, 2021).

3. Artificial intelligence and education: the state of the art

In order to describe the current research and achievements of AIED, let us refer to some aspects that allow us to outline a framework of understanding. Specifically, we try to:

- provide some data about AIED;
- indicate its theoretical foundations and practical implications.

3.1. Data about AIED

Chen, Zou, Xie, Cheng and Liu (2022), on the basis of 4,519 publications from 2000 to 2019, attempted to identify trends and critical issues in AIED. The results of the study, on a statistical basis, reveal interesting aspects, including a growing interest in the use of AI for educational purposes.

Chart 1 shows the number of articles on AIED published from 2000 to 2019, indicating a general upward trend, particularly since 2012, indicative of an expanding scientific community and output (Chen *et al.*, 2020; Hinojo-Lucena *et al.*, 2019; Roll - Wylie, 2016; Tang *et al.*, 2021; Zawacki-Richter *et al.*, 2019). The growing interest in AIED research has been mainly attributed to the increasing positive findings of the effects of AI on performance and learning goals achieved. Specifically, research on AIED is particularly valued by interdisciplinary journals such as «Computers & Education» and «Educational Technology & Society», with their dual focus on education and technology. These journals also rank very well for publications on AI in e-learning (Tang *et al.,* 2021). The results support the hypotheses put forward by Zawacki-Richter *et al.* (2019) and Tang *et al.* (2021), who highlighted the close relationship of AIED with computer science and software engineering.

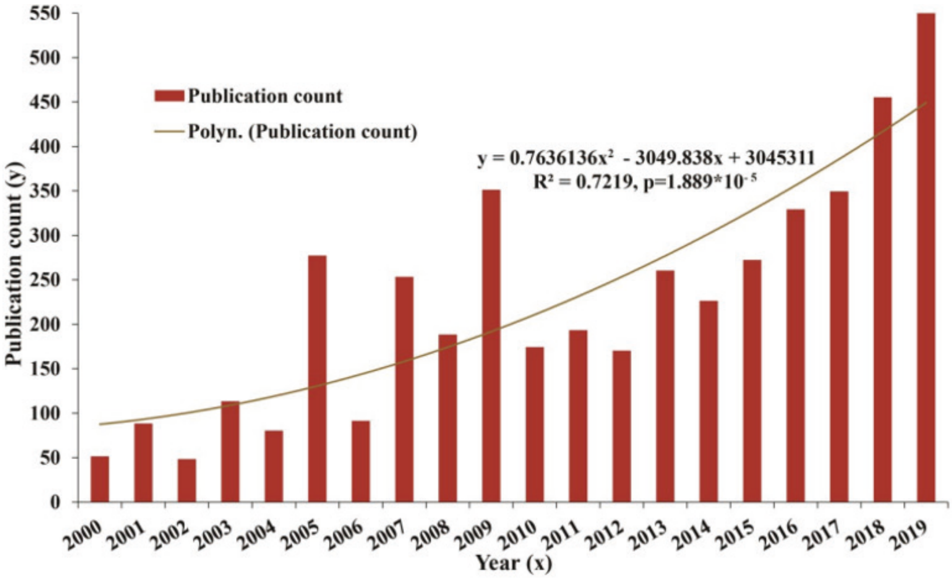


Chart 1 - Number of AIED publications year by year (2000-2019).

Figure 1 shows the collaborations between the main countries/regions on AIED. In particular, United States, United Kingdom, Canada, Spain and Australia were the most collaborative. Hinojo-Lucena *et al.* (2019) identified US, Canada, UK and Taiwan as the countries most interested in AIED. Here, the higher research productivity can be attributed to their governments' efforts to promote AI-enhanced learning. In addition, the interdisciplinarity of AIED was highlighted as a strength by demonstrating how the most effective AI technologies in education originated from a cross-disciplinary research experience.

Fig. 1 - Collaborations between the main countries/regions on the subject of AIED

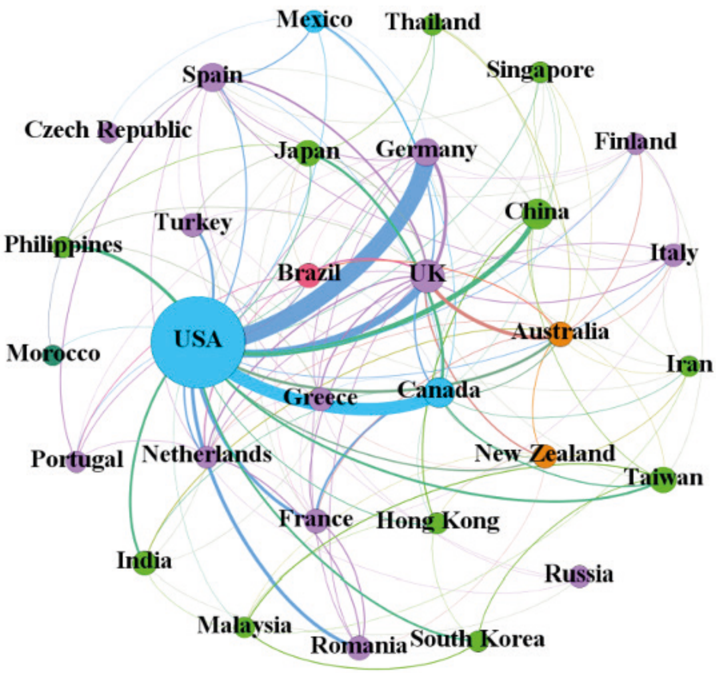
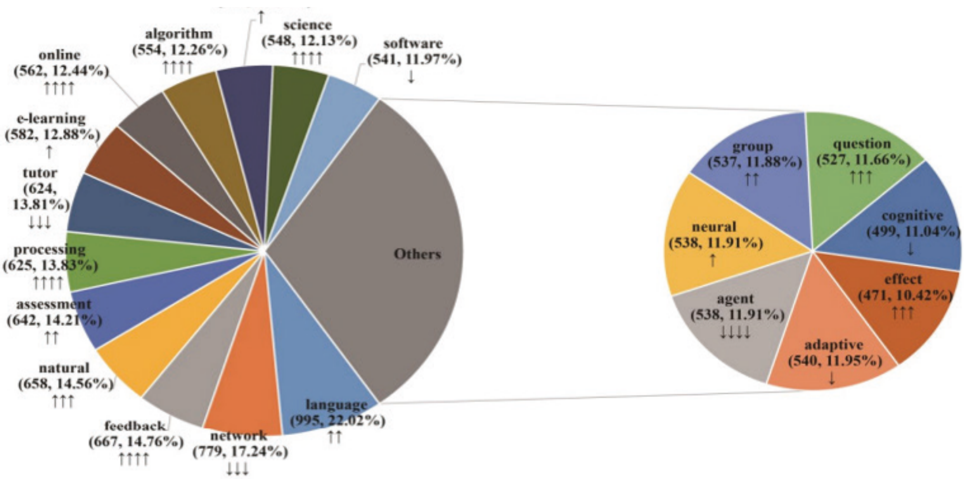


Figure 2 shows the twenty most frequently used terms in a sample of 995 publications on AIED. The term 'language' appears to be the most investigated, followed by 'network', 'feedback', 'natural' and 'evaluation'. In particular, a trend test showed that the terms 'language', 'feedback', 'natural', 'evaluation', 'processing', 'online', 'science', 'group' and 'question' continue to have significant increases.

Fig. 2 - Most frequently used terms in a sample of articles about IAED



Note. inside the parentheses are term occurrence and proportion; ↑(↓): increasing (decreasing) trend but not significant ($p > .05$); ↑↑(↓↓), ↑↑↑(↓↓↓), ↑↑↑↑(↓↓↓↓): significantly increasing (decreasing) trend ($p < .05$, $p < .01$, and $p < .001$, respectively)

Fig. 3 - Research topics and trends

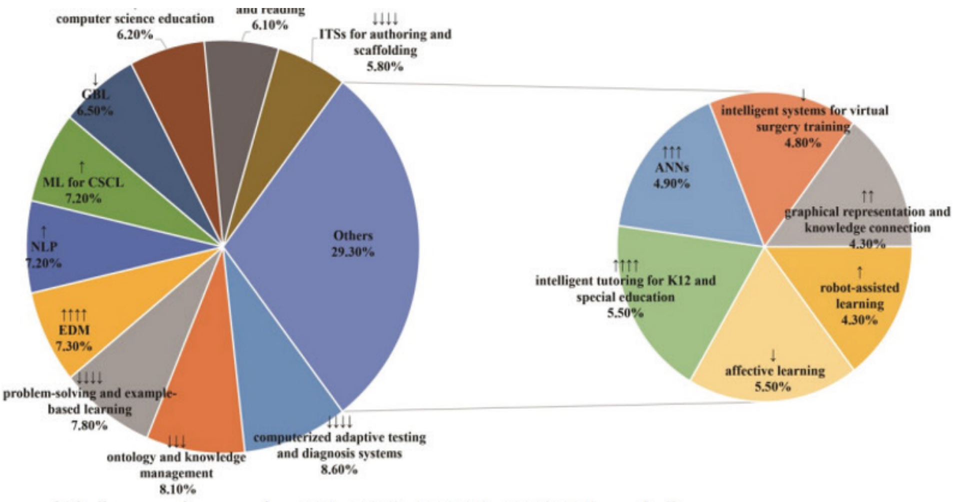


Figure 3 shows the sixteen most frequently discussed topics in research on AIED, accompanied by the results on trend tests. Specifically, the five most relevant topics, with a significant upward trend, are: 'educational data mining (EDM)' (1); 'intelligent tutoring for writing and reading' (2); 'intelligent tutoring for K12 and special education' (3); 'artificial neural networks (ANNs)' (4); 'graphical representation and knowledge connection' (5). Conversely, the four topics that have experienced a significant downward trend over the two decades are: 'computer adaptive testing' (1), 'ontology and knowledge management' (2), 'problem-solving and problem-based learning' (3), and 'ITS for authoring and scaffolding' (4). All of these systems facilitate the achievement of various educational goals, such as subject knowledge (e.g. language skills and programming), skill acquisition (e.g. problem-solving) and the implementation of innovative pedagogical strategies (e.g. Game Based

Learning, BL and example-based learning). Several reviews (Chassignol *et al.*, 2018; Guan *et al.*, 2020; Tang *et al.*, 2021; Zawacki-Richter *et al.*, 2019) have acknowledged the important role of ITS and AI in assessing, feedbacking and predicting student performance, supporting collaborations in interactive learning, also assisted by instructional robots. Roll - Wylie (2016) and Tang *et al.* (2021) highlighted a growing interest in learning at the knowledge domain level, such as language and medical education and STEM learning.

Briefly, topics that will be increasingly relevant are: EDM for performance prediction, NLP for language education with a focus on intelligent tutoring for writing and reading, visual knowledge representation, affective computing for affective learning, as well as recommendation systems for personalized learning (Guan *et al.*, 2020).

3.2. Theoretical foundations and practical implications

Ouyang and Jiao (2021) refer to three paradigms elaborated from research to sketch an evolution of AIED with respect to learning/teaching theories, with a focus on AI techniques, from the oldest to the most widely used today. Table 1 summarizes the three paradigms with reference to their theoretical foundations and practical implementations .

Let us try to say something about each of these three paradigms.

The first one is characterized by an AI-directed approach and conceives of the learner as a receptor: AI directs the learning process, while learners act as receivers to follow specific learning paths. The theoretical foundation is the theory of behaviorism, which emphasizes the construction of carefully organized content sequences that lead to correct learner performance (Skinner, 1953). Learning occurs by reinforcement of knowledge acquisition through programmed instructions that introduce new concepts in a logical and incremental way, provide the learner with immediate feedback on incorrect responses and maximize positive reinforcement (Greeno *et al.*, 1996; Schommer, 1990). Specifically, AI systems inherit the characteristics of Skinner's (1958) learning machine (Burton-Bartlett, 2004). Examples of applications of this paradigm are intelligent tutoring systems (ITS) such as

Table 1 - IEAd paradigms (Ouyang - Jiao, 2021)

	Theories	Implementations	AI Techniques	Exemples
AI-directed, learner-as-recipient	Behaviorism	Intelligent Tutoring Systems (ITS)	AI based on relational statistic techniques	ACT Programming Tutor (Anderson *et al.*, 1990); Stat Lady (Shute, 1995)
AI-supported, learner-as-collaborator	Cognitivism Socio-constructivism	Dialogue Tutoring Systems (DTS); Exploratory Learning Environments (ELE)	Bayesian networks, NLP, Markow decisional trees	Exploratory Environment QUE (Metzler - Martincic, 1998)
AI-empowered, learner-as-leader	Connectivism Complex Adaptive Systems	Human-machine cooperation, adaptive/personalized learning	Brain-computer interface, automatic learning, deep learning	Real time MOOC through predictive modelization (Lee *et al.*, 2018)

Stat Lady, a statistics tutor that presents all the curriculum content in a fixed order and requires students to solve a predefined set of problems before assuming mastery and thus moving on to the next stage (Shute, 1995). An intelligent version of *Stat Lady* assesses students' input knowledge on the basis of an online pre-test, uses various methods to represent students' learning stages and makes decisions on the need for remedial action accordingly (Shute, 1995). AI is based on statistical-relational techniques and acts as a director of the entire learning process; students receive support in conducting cognitive investigations, solving problems and achieving learning goals. Since it is the system that defines the content and path of learning, an open problem with respect to an AI use of this kind (du Boulay, 2019), concerns an effective understanding of how much and what information is needed to correctly represent, assess and guide students' acquisitions in terms of knowledge and skills.

The second paradigm is characterized by an AI-supported approach and conceives the learner as a collaborator: the AI system relinquishes its power of control to act as a support tool, while learners work as collaborators to focus on the learning process. This paradigm is based on the second cognitivist and social constructivist view of learning: in this perspective, learning occurs when a learner interacts with people, information and technologies in socially situated contexts (Bandura, 1986; Liu - Matthews, 2005; Vygotsky, 1978). Consequently, the AI system and the learner should build active interactions to optimize personalized learning. Specifically, the AI system collects learners' emergent and individualized information as input to adaptively optimize the learner's model, while learners act as collaborators to communicate with the AI system in order to achieve better or more efficient learning (Baker *et al.*, 2019; du Boulay, 2019; Rose *et al.,* 2019). Different implementations of AI, such as dialogue-based tutoring systems (DTS) or exploratory learning environments (ELE), have been developed to achieve reciprocal interactions between the system and the learner. For example, Stamper (2006) used a Markov decision process to automatically generate production rules using the learner's previous data on a problem set and to continue refining the production rules as the learners generated new data. Furthermore, Käser *et al.* (2017) made use of dynamic Bayesian network models to represent learners' multiple skills hierarchies and the relationships between different skills, improving the accuracy of the learner's knowledge representation. On the other hand, the learner can communicate with the system to understand its decision-making process and make better choices for further learning. Of particular interest is an exploratory environment called *QUE*, designed to allow learners to explore discrepancies between incorrect answers and system knowledge. In this case, the learner explores the reasoning processes of the intelligent system by asking questions such as "Why not" and "What if", which are fundamental for explaining or understanding reasoning processes in an interactive learning situation (Metzler - Martincic, 1998). The main problem with this paradigm is to understand to what extent and how student information is integrated into the AI system to optimize the student model, reflect various aspects of the learning state and develop adaptive and AI-supported learning and instruction. The general problem is the lack of continuous communication or synergistic interactions between humans and computers.

The third and last paradigm is characterized by an AI-empowered approach: the learner's agency is at the heart of AI (Bandura, 2006) and AI is seen as a tool to increase human intelligence (Law, 2019). This embraces the perspective of complexity theory, which sees education as a complex adaptive system (Mason, 2008), in which synergistic collaboration between multiple entities (e.g. the learner, the teacher, information and technology) in the system is essential. In this complex system, AIED must be designed and applied with the understanding that AI techniques are part of a larger system (Riedl, 2019). Concepts such as human-computer co-operation (Hoc, 2000), human-centered AI and ML systems (Riedl, 2019), human-AI collaboration (Hwang *et al.*, 2020), and educational community-centered AI (Yang *et al.*, 2021) highlight the importance of AI from a human-centered perspective that takes into account people's conditions, expectations and life contexts. Within this third paradigm, AI assists students and teachers in achieving augmented intelligence by providing a high level of transparency, accuracy and effectiveness (Riedl, 2019; Yang *et al.,* 2021). The teacher is equipped with understandable and interpretable AI devices to facilitate learner-centered activity (Baker *et al.*, 2019; Holmes *et al.*, 2019; Roll - Wylie, 2016). The learners assume the role of 'leader' of their own learning, manage the risks of AI decision automation and develop better or more efficient learning (Gartner, 2019). The development of advanced interaction techniques, such as smart wearable devices, cloud computing and the Internet of Things, change the way humans interact with AI systems (Pinkwart, 2016; Xie *et al.,* 2019). Lee *et al.* (2018), for example, built a deep learning model with recurrent neural network classification to perform real-time predictive modeling of MOOCs and provide personalized communication capabilities between teacher and learners. And again, Cukurova *et al.* (2019) used prediction models and classification algorithms to increase the transparency of expert tutors' decision-making processes to give advanced feedback. This innovative work attempts to use human-machine cooperation to enable teachers to make a more accurate prediction and analysis of learners' further participation and provide them with personalized guidance (Blikstein, 2018; du Boulay, 2019; Tang *et al.*, 2021).

4. *AI and the curriculum: the ESLAI framework and AI culture in schools*

One of the themes of AIED is how to imagine integrating AI culture into school curricula (Eliott, 2019) to support citizenship behaviors in the code society.

The four dimensions on which such a culture rests are the literacy, critical, ethical and expressive dimensions. Talking about the literacy dimension means referring to languages: it is not only about computer skills, or writing code; it is also the lexicon of AI that needs to be developed, the understanding of how it works, both in front of and behind the interfaces (Ng *et al.*, 2021). The critical dimension has to do with awareness: the ability to shift through information, be it text or images, considering that AI applications make the fake even more credible (Information Literacy); the ability to manage one's own data when interacting with platforms (Data Literacy); the attitude of suspicion towards a presence that is as pervasive as it is invisible (Ibna Seraj - Oteir, 2022). The ethical dimension has to do with responsibility. In this case, the user rather than as a user of AI is regarded as an active user: responsibility implies respect for rules and for the others, considering the consequences of one's choices and actions. Finally, the expressive dimension concerns the possibility of creating artifacts with AI applications (Borenstein - Howard, 2021). Here lies the great theme of authorship, or rather, co-authorship between humans and machines (Panciroli - Rivoltella, 2023), with what it can open up for generative processes.

Dimensions	**Skills**	**Learning goals**
Literacy	Making code, knowing the vocabulary	Experience
Critics	Managing data, sifting information Awareness	Awareness
Ethics	Respect rules and others	Responsibility
Espression	Producing texts and images	Autorship

Table 2 - AI culture: dimensions, skills, criteria.

These four dimensions are a first element from which to think about the construction of an IA curriculum: they are the levels at which pupils are asked to develop skills and against which the educational goals that the curriculum intends to promote at the end of each class or school segment to which we are referring can be measured. In order to operationalize them, it is necessary to adopt a criterion that allows for their design on both the macro and micro levels.

Such a criterion can be found in the internal organization of Situated Learning Episodes (Rivoltella, 2013; 2016; 2023), as we have already tried to show by setting up the ESLAI Framework together with colleagues from the Institute of Education Technology by CNR in Palermo (Panciroli *et al.*, 2023). The three phases of which ESL consists - preparatory, operational, restructuring - are based on modalizing verbs that can function at both the macro and micro levels: anticipate, produce, reflect[3].

The micro level is already explicit in the structure of ESL. This means that, in lesson planning, the teacher starts by designing an activ-

[3] In Greimasian semiotics, a verb is modalizing insofar as it refers to the attitude adopted by the speaker with respect to his utterances (Greimas, 1983). In this case, the three verbs of ESL are modalizing insofar as they refer to and describe the action of the learner in relation to the activities proposed to him/her.

ity that enables students to make use of cognitive anticipation (Riegler, 2001), then sets up a small-group activity leading to the realization of an artifact, and finally imagines the metacognitive discussion of what has emerged and the lesson afterwards (Watson - Williams, 2004). The belief is that this design also proves effective in the case of teaching with and about AI. An example will help to understand better. Let us imagine that we are in a Human Sciences class at the High School and that we intend to design an ESL on Artificial Intelligence involving several disciplines: Human Sciences, Philosophy, English, Law and Economics. The preparatory activity asks students to interact with *Chat GPT* to find out what it thinks about the use of digital devices before the age of three. In the operational phase, students are asked, divided into small groups, to analyze *Chat GPT*'s response in search of possible bias. In the meantime, they have asked Gemini to do a research on what literature says about the same issues. The result of the operational phase will be a new prompt asking *Chat GPT* to reformulate its point of view. In the restructuring phase, the class will be asked to evaluate *Chat GPT*'s new response and relate it to the first one and the review produced by Gemini in order to bring out any cognitive conflict (Lee - Yi, 2013). Table 3 shows how the different Teaching and Learning Activities into which the ESL is divided are distributed in relation to the four dimensions of AI culture and the three modalizing verbs of ESL.

<table>
<tr><th>Dimensions/ Verbs and phases</th><th>Anticipate (Anticipatory phase)</th><th>Produce (Operational phase)</th><th>Reflect (Debriefing phase)</th></tr>
<tr><td>Literacy</td><td>Train prompting skills in dialogue with Chat GPT</td><td>Build, thanks to Gemini, a map of scientific research viewpoints on the topic</td><td></td></tr>
<tr><td>Critics</td><td></td><td rowspan="2">Analysing the response provided by Chat GPT, looking for commonplaces and biases</td><td>Discuss Chat GPT's new proposal, also in the light of literature, and establish the class's point of view on the subject by bringing out any cognitive contrast between the points of view</td></tr>
<tr><td>Ethics</td><td></td><td></td></tr>
<tr><td>Espression</td><td>Ask Chat GPT to articulate its point of view in relation to the use of digital devices before age 3</td><td>Based on the critical issues that emerged, construct a new prompt to ask Chat GPT to respond and reformulate their point of view</td><td></td></tr>
</table>

Table 3 - An example of micro-design on AI

At the macro level, however, the framework "forces" the ESL device, designed for lesson planning, so that it can also work in the organization of the curriculum. This is helped by the three modalizing verbs that, all of them, may have to do with AI-related skills.

Anticipating, in the case of AI, can mean using apps to make predictions (McGarr, 2021), or to simulate scenarios (one thinks here of their use in economics, or in biology, but also in all technical disciplines), to generate provisional summaries of a content (to which one can return after the teaching activity to verify deviations and possible cognitive conflicts), to produce visual representations of phenomena in different forms.

Producing mainly involves the use of generative AI applications to support different teaching activities: the production of text in different languages, the generation of images, the creation of videos or music (Baidoo-Anu - Ansah, 2023). But, on a technical level, 'doing AI' also means developing programming skills, building a dataset, knowing how to train an algorithm (Rodriguez-García *et al.*, 2020), the latter being the responsibility of the technical disciplines and which can be developed specifically in computer science classes.

Finally, *reflecting* involves developing critical awareness of how AI works: reasoning about data, how it is collected and used, identifying bias, recognising business logic and underlying policy implications (Leander - Burriss, 2020).

Again, the example in Table 4 will help to better understand how the framework works. The visualization - with the four dimensions of AI culture on the vertical axis and the three ESL modalizing verbs on the horizontal axis - should help the teacher in her/his design activity. In the boxes the skill goals are described; for completeness, the learning goals should also be included.

	Anticipating	**Producing**	**Reflecting**
Literacy dimension	Searches for information, data and content to generate effective prompts	Manages information, data and content to generate effective prompts	Assigns a criterion of effectiveness to the prompts used
Expressive dimension	Selects AI applications for specific purposes, including professional purposes Identifies possible areas for the creation of digital artefacts with AI	Uses AI applications for specific purposes, including professional purposes	Analyses and reflects on AI applications in relation to the products they enable
Ethical dimension	Analyses the social implications of AI systems in personal and professional contexts in relation to the adoption of an application	Uses AI applications considering their social implications	Reflects on the social implications of AI systems in personal and professional contexts in a system logic
Critical dimension	Assesses possible scenarios resulting from the use of AI in a simulation logic	Uses critical analysis tools on processes and products involving the use of AI	Critically evaluates the outputs obtained

Table 4 - An example of AI macro-design for class IV, Secondary School

5. Conclusion: future challenges

In closing, let us try to indicate what the future challenges are for AIED research.

Firstly, as AI in education is a relatively recent field of study and application (Holstein *et al.*, 2017), resulting in widespread mistrust (Lin *et al.*, 2017), it is necessary to work on increasing confidence in this field. One way to succeed in this is to demonstrate the effectiveness of AI systems through impactful experiments, referring to the pedagogical theories that validate their theoretical settings as well as their practices. Researchers should go beyond the analysis of how AI can improve learning in different subjects to also examine improvement in specific skills (e.g. self-efficacy and higher-order thinking).

A second priority is to try to match the complexity of the learning process and educational systems with the complexity of AI systems. This requires AI to be designed and managed in such a way as to offer effective communication tools to gather the values and interpretations of all stakeholders, align AI models and make goals compatible with learner-centered learning (Knox *et al.*, 2019; Rowe, 2019; Segal, 2019). This requires involving data scientists as well as non-technical stakeholders, such as teachers and educational experts, in the design and prototyping activity (Holstein *et al.*, 2018).

A third priority is related to the development of new literacies and new tools for exercising critical thinking about the reality of data and algorithms. AI, from this point of view, represents a strong discontinuity respect on even the recent history of media development, and this requires fundamentally revising what Media Literacy Education had traditionally developed in this regard.

* * *

Il Numero di questa Rivista che abbiamo il piacere di presentare conta 12 contributi provenienti da università e centri di ricerca (l'INDIRE, l'ITD del CNR). La loro distribuzione all'interno del Numero segue una ideale tripartizione: prima i contributi di quadro, poi quelli che si chiedono cosa cambi con l'IA nell'educazione, infine gli articoli dedicati a singole specifiche questioni.

Il primo contributo, di Alessandro Soriani e Paolo Bonafede, fornisce un'ampia ricognizione sul significato dell'AIED e produce riflessione sul significato e i modi dell'introduzione dell'IA in scuola. L'obiettivo è di produrre una «*forma mentis*, nella relazione con le tecnologie IA […]. Capire e attivare consapevolezza circa il come, il perché, il significato, gli effetti, i benefici, cosa si "perde" e cosa si "guadagna", deve diventare prassi nelle scuole: si tratta di costruire, allenare, ed esercitare quotidianamente, nell'utilizzo di strumenti IA, una postura di "artigianalità" che non rinunci a questi interrogativi».

Il contributo di Maila Pentucci *et al.* presenta un'interessante ricerca in cui l'IA diviene strumento di indagine nella prospettiva dei Cultural Analytics. Gli artefatti di 560 studenti di Scienze della Formazione primaria vengono sottoposti a un'analisi su tre livelli: manuale, linguistico, computazionale. L'interesse dell'articolo sta nel mostrare cosa l'IA possa apportare alla ricerca basata su analisi testuale.

Nel loro articolo, Salvatore Messina *et al.* conducono una systematic review sullo stato dell'arte dell'AIED oggi. L'esito è una mappatura interessante (e utile) per orientarsi all'interno degli indirizzi di ricerca più attuali sul rapporto tra l'Intelligenza Artificiale e la scuola.

Sempre al mondo della scuola si rivolge l'attenzione di Perna *et al.* che adottano il modello della Actor-Network Theory, mutuato da Bruno Latour, per analizzare i cambiamenti che l'adozione dell'AI produce sulla relazione tra insegnanti e studenti in classe. Nello studio una particolare attenzione viene dedicata al caso dell'AI generativa.

Sempre riflettendo sulle trasformazioni imposte dal ricorso dell'AI nelle pratiche di scuola, Manuel Gentile *et al.*, nel loro contributo, presentano i risultati provvisori di un progetto europeo – AI4T – che ha sperimentato un modello per la formazione degli insegnanti di scuola in tema di Intelligenza Artificiale. L'articolo presenta il piano della formazione e lo analizza dal punto di vista dei pro e contro fornendo un'ipotesi praticabile che si offre per la sperimentazione in contesto.

Il contributo di Giuseppina Rita Jose Mangione e Francesca De Santis porta l'attenzione sul rapporto tra IA e piccole scuole. Le autrici sono ricercatrici presso l'Istituto Nazionale per la Documentazione e la Ricerca Educativa (INDIRE) che da anni porta avanti un lavoro di ricerca e supporto sulle e alle cosiddette piccole scuole: scuole di montagna, rurali, delle isole minori, spesso caratterizzate dalla presenza di pluriclasse. L'articolo restituisce i risultati di un doppio percorso di indagine: una scoping review sulla presenza del tema nelle riviste internazionali e una riflessione parlata condotta con un gruppo di esperti a livello nazionale.

Muovendo dalle istanze di boyd e Crawford (2012), che manifestano la necessità di integrare la Data Literacy nella Media Literacy, l'articolo di Andrea Garavaglia e Livia Petti propone un'indagine sulla possibilità di analizzare le produzioni mediali generate da agenti intelligenti attraverso l'adattamento degli approcci mediaeducativi utilizzati per realizzare interventi educativi sui media tradizionali e sui new e social media integrati a un framework di data literacy. Si tratta di considerare l'analisi della produzione e comunicazione mediale, non più generata solo da redazioni, specialisti, influencer e prosumer, ma anche da applicativi di Intelligenza Artificiale (IA) per la produzione mediale automatizzata.

L'articolo di Elisa Farinacci riflette sui rapporti tra cinema e Intelligenza Artificiale. Il punto di partenza verte sull'economia del cinema e ragiona su come cambino le logiche della produzione con l'avvento dell'IA. L'analisi prosegue con una mappatura campionaria di alcuni dei software che oggi consentono di rivoluzionare molti settori dell'industria cinematografica: dal casting, alla sceneggiatura, al design dei costumi e della scenografia. Il punto di approdo provvisorio della ricerca di Elisa Farinacci è la definizione di un nuovo paradigma per l'Audiovisual Literacy, l'AIAL (Artificial Intelligence Audiovisual Literacy): un'ipotesi di lavoro che attende di essere discussa e applicata.

L'articolo di Luna Lembo *et al.* restituisce gli esiti di una ricerca condotta nel contesto del laboratorio sperimentale di Francesco Peluso Cassese presso UniCusano. Il tema è il ricorso ai Google Lens a supporto dell'apprendimento di soggetti con DSA. Lo studio pilota che viene presentato, per quanto condotto su una numerosità ristretta di soggetti, non conferma quanto contenuto nell'ipotesi di ricerca e cioè che tale dispositivo presenti enormi potenzialità in funzione degli apprendimenti. La spiegazione di tale risultato viene trovata dagli autori nella necessità di lavorare sulla composizione del dataset e sul training del sistema di IA che sta dietro al dispositivo. Questo è particolarmente vero nel caso di soggetti con DSA e in particolare con disgrafia, poiché la loro scrittura si discosta significativamente dagli esempi di scrittura standard su cui verosimilmente il training del dispositivo è stato svolto.

Il contributo di Greta Persico e Martina Rosola verte sull'applicazione in ambito educativo di un correttore automatico per l'italiano progettato per facilitare l'adozione di un linguaggio gender fair nei documenti amministrativi. L'analisi mostra il duplice vantaggio dell'adozione di questo strumento: da un lato, produce testi fair e, dall'altro, aiuta gli utenti a sviluppare la capacità di riconoscere e sostituire le espressioni sessiste diventando in qualche modo un tool educativo.

Gli studi sull'odio sono uno dei campi interdisciplinari in cui l'intelligenza artificiale viene applicata alla ricerca di algoritmi per individuare i discorsi d'odio online. L'articolo di Stefano Pasta si propone di evidenziare il ruolo delle tecniche di classificazione umana nella ricerca dei discorsi d'odio online attraverso l'apprendimento automatico e la logica computazionale. L'occasione è un caso di studio basato sull'antisemitismo su *Twitter* durante il periodo della pandemia (2019-2021). I tweet sono selezionati in italiano e vengono analizzati con tecniche di social network analysis (SNA). I risultati sono poi sottoposti a una matrice di confusione, uno strumento utilizzato per analizzare gli errori commessi da un modello di apprendimento automatico, al fine di trarre considerazioni metodologiche sul rapporto tra logica algoritmico-computazionale e classificazione umana.

Valeria Caggiano ed Ema Di Petrillo, infine, nel loro articolo riflettono sulle tecnologie educative intelligenti. Si tratta di un settore in rapida crescita che utilizza strumenti e software digitali per supportare e migliorare le esperienze educative di studenti ed educatori grazie al contributo dell'intelligenza artificiale. L'articolo presenta uno studio di caso di innovazione del curricolo in una business school, sottolineando le implicazioni pedagogiche e il dialogo con le parti interessate.

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