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ARTIFICIAL INTELLIGENCE IN EDUCATION: SCIENTIFIC INTERPRETATIONS AND PEDAGOGICAL IMPLICATIONS

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Artificial intelligence is one of the most significant epistemological and technological transformations of the 21st century, with increasing impact on education. AI is not only technically interesting; it has also brought about huge cognitive shifts, which are related to intelligence, knowledge, and learning in general. In the scope of this paper, we also discuss scientific thoughts on artificial intelligence with respect to symbolic, connectionist, and generative paradigms as applicable in education. The methodology is based on theoretical-conceptual reasoning and also an integrated review in the field of computer science, cognitive science, and technological studies. In theory and in practice, we show how AI is evolving to have effective learning as well as learning ability at the same time (that is the way in which it helps self-led learning). So, our conclusions emphasize the necessity of an appropriate and reasonable application of artificial intelligence to education and to be responsible for education and that it can be in line with the teachers in its training and education in a supportive manner, albeit with the teacher’s role.

Keywords: *Artificial intelligence, education, machine learning, deep learning, digital pedagogy, personalized learning, ethics of artificial intelligence.*

INTERPRETĂRI ȘTIINȚIFICE ACTUALE ALE INTELIGENȚEI ARTIFICIALE

Inteligența artificială a devenit una dintre marile schimbări epistemologice și tehnologice ale secolului XXI, având un impact din ce în ce mai important asupra vieții și educației. Ea depășește aspectele sale tehnice pentru a modifica unele dintre mentalitățile noastre și pentru a înțelege ce înseamnă inteligența și cum doresc oamenii să fie aceasta. În lucrarea de față, prezentăm percepția științifică a inteligenței artificiale (și pentru o zonă globală) cu ceea ce suntem capabili să folosim și ceea ce știm despre inteligența artificială prin utilizare și cercetare. Vom realiza analiza teoretică în cercetare și vom face o revizuire integrativă a ultimului deceniu de științe ale calculatoarelor, științe cognitive și perspectivă tehnologică (cu un accent deosebit pe analiza pedagogică) și apoi vom prezenta ceea ce sunt teoriile probabilistice emergente și teoriile, și cum vom reieși din teoria inteligenței artificiale. Concluziile clarifică faptul că integrarea inteligenței artificiale în educație ar trebui considerată ca un mijloc de promovare a procesului de învățare cu ajutorul cadrului în care se bazează învățarea.

Cuvinte-cheie: *Inteligență artificială, educație, învățare automată, învățare profundă, pedagogie digitală, învățare personalizată, etica inteligenței artificiale.*

Introduction

Artificial intelligence can no longer only be known as a technical field in computer science, but as something to be seen as an artificial cognitive infrastructure restructuring the knowledge production, validation, distribution and learning processes. These changes affect not only access to information but more importantly the structure of teaching and learning in the classroom. From its early days in the second half of the twentieth century to the present day with the development of high-quality language models, the field of AI is undergoing rapid advances - which it has never had in the past.

Classical definitions associated artificial intelligence with individuals who act according to a set of objectives [12]. And for this reason, a functionalistic view focused only on performance and decision-making efficiency. From now on for artificial intelligence, especially in the field of deep learning and generative models, we cannot define artificial intelligence purely by its behavior. In schools, learning from what people do and learning based on what they see is important.

Artificial intelligence works in today’s world by accessing huge quantities of data and optimizing complex mathematical functions, resulting in output similar to creativity, semantic understanding, and (even) logical argumentation. In education, such capabilities bring in new forms of personalized learning, adaptive teaching, and automatic feedback (and so on), which do raise a whole lot if not more questions about the ethics and morality of learning. What intelligence is actually produced by artificial intelligence?

To answer this question, we need to assess current scientific and academic views about AI development and how they apply in practice to the learning process.

Theoretical foundations of artificial intelligence
From Symbolic Formalism to Distributed Processing

In fact, early models and theories of artificial intelligence were essentially based upon a comparison between human reasoning and the use of symbols. In such models, intelligence is viewed as the application of logic to non-intellectual representations [12, p. 19-22]. Expert systems, established in the 1970s and 1980s, were based on knowledge bases and deductive inference methods, and are believed to have originally evolved as a means of formalizing the processes of instructional and rule-based learning.

This encouraged the era with hopefulness that knowledge itself would be fully formalized. But the way that implicit knowledge, ambiguity and its contextual variations were represented suggested in this work showed that the rigid formalism still failed in many aspects. And for the education world, these difficulties were evident as social and cognitive reality were too complex to encapsulate precisely within these rules in terms of how they worked out and how they understood knowledge and understanding in students.

On the other hand, the connectionist perspective suggested a nonlinear model of information processing based on artificial neural networks. Artificial neural networks do not implement symbolic rules, so their weights are determined by the simple mathematical units of neural networks [8, p. 1528-1530; 9, p. 437]. Learning is an iterative optimization and the representations become flexible rather than fixed [6, p. 3-6; 9, p. 438]. On the other hand, this type of connectionist model is part of the evolution of flexible education processes and data-driven learning environments.

This change marks a radical epistemological shift since knowledge will no longer be considered in advance, but will be incorporated into model parameters [6, p. 7-9]. In that sense, it raises fundamental questions about how knowledge is received, transmitted and interpreted in digital learning paradigms.

Table 1. Analytical Matrix of the Evolution of Artificial Intelligence Paradigms and Their Relevance for Educational Processes

Dimension of Analysis	Symbolic Paradigm	Connectionist Paradigm	Generative Paradigm
Ontology	Intelligence as symbolic manipulation	Intelligence as distributed process	Intelligence as probabilistic emergence
Epistemology	Deductive	Inductive	Predictive-probabilistic
Type of Representation	Explicit	Distributed representations	High-dimensional vector representations
Explanation / Prediction Ratio	Priority of explanation	Balance	Priority of prediction
Degree of Transparency	High	Medium	Low
Fundamental Limitation	Logical rigidity	Lack of explainability	Lack of causality
Educational Implications	Structured instruction, rule-based teaching, teacher-centered learning	Adaptive learning, personalized feedback, learner-centered approaches	Automated content generation, intelligent tutoring systems, AI-assisted learning environments

În această comparație, am arătat o varietate de abordări ale inteligenței artificiale, care vor fi importante pentru condițiile educaționale. Sistemele de învățare simbolică și sistemele de învățare bazate pe reguli fac învățarea mai structurată sau clară, în timp ce structura educațională a conexiunilor va permite elevului să învețe independent și mai abil, iar învățarea generativă va introduce, de asemenea, dezvoltarea automată de conținut și sistemele de învățare asistate de IA. We must take into account these differences to know how artificial intelligence shapes the pedagogic model today.

Deep Learning and the Emergence of Hierarchical Representations

Deep learning has revolutionized how neural networks process complex data [9, p. 436]. The models based on multiple layers of processing work on building up complex hierarchical representations from the raw data [6, p. 3-5; 9, p. 437]. For instance, in the visual domain, the first layers identify the simplest features, while higher layers combine these features into abstract structures [6, p. 14-16]. In the education fields, this type of processing can be able to understand student performance and work towards more flexible learning pathways on the basis of individual needs as a whole.

With this level of automatic abstraction, we have been able to design systems to do very special and complex activities, like image classification or biomedical analysis, to be able to outdo human performance as well [13, p. 484-486]. In education, similar mechanisms are used in learning analytics and intelligent tutoring systems. But high performance comes with opacity on decision making. The models are the kind of complex machines that can get confused and the transparency and accountability of such automated feedback and assessment should also be ensured by such platforms and methods of assessment [10, p. 118-121].

Generative Models and Semantic Simulation

The advent of transformer architectures helped revolutionize the field of natural language processing [15, p. 5998-6000]. Large-scale language models are trained on massive text domains and are capable of generating a coherent linguistic sequence based on the probability distribution of tokens [6, p. 62-65; 15, p. 6001-6003]. In the educational world, they generate learning materials, support writing, and help language learning activities.

The work of those systems does not take concrete conceptual knowledge into account but just an idea that seems to be coming through (as indicated by probable continuation of them as a mathematical concept). Nevertheless, the results they can produce in fact simulate logical argumentation and discursive coherence [10, p. 146-150], which raises important questions regarding authorship and originality of learners’ accomplishments.

This will create interpretative tension. When a system is producing coherent and contextually appropriate texts, how can we refer to understanding? This question is important in education and does so directly affect our knowledge performance and student interaction for that purpose. To differentiate between simulation and comprehension is necessary in order to conceptualize artificial intelligence in a way that can be understood, and so will being successful in educational practices [5, p. 45-49].

Probabilistic Epistemology and the Transformation of the Concept of Knowledge

One of the most profound impacts of the recent growth of artificial intelligence is the displacement of scientific knowledge. Knowledge has for a long time been about causal explanation of the phenomena and the construction of theories that can reason and explain what happened. Now machine learning, however, puts the emphasis on prediction as compared to explanation, which is what people do [9, p. 436-438]. In the education field, the rise of predictive analytics for performance and adaptation is also happening.

Many such modern models look for statistical regularities within a massive dataset in order to find a loss function and subsequently adjust parameters so as to minimize prediction error [6, p. 92-96]. In this way, we think the success of a system is not in terms of its ability to reason (expected explanation), but of its predictive capacity [6, p. 98-101]. It is with educational frameworks in place that we find focus on results more than conceptual understanding.

This mutation has major epistemological implications. Knowledge depends on data and its validity has to do with how efficient the system is at doing the work [10, p. 118-121]. In this model, truth is practical, and if a model works in a given system, then it is valid, and more and more evidence is added every time we use it because the context has to be right. But in education, this calls for some worrying questions about generalization, that some of the knowledge can be learned and transferred into other contexts [10, p. 154-158].

The correlation versus causation issue becomes central. Most deep learning systems are learning to identify correlations and connections and thus are unable to distinguish between genuine causal relations and mere statistical coincidences [11, p. 19-23]. The lack of causal modeling makes it less certain these systems really work and are effectively employed in real-world places like schools and even the workplace [11, p. 47-52].

Thus, the epistemology emerging in artificial intelligence is probabilistic, inductive, and performance-driven. This reconfiguration of the concept is a call not only from the scientific and technological backgrounds but also to education systems in order to re-examine the relationship between theory and practice, and between knowledge and learning processes [11, p. 65-70].

The Ontological Dimension

Besides epistemological developments, artificial systems present existential questions for education and pedagogical practice. Artificial intelligence in education and school policy as far as we know has to do with the type of entity which makes life possible. Can an artificial intelligence system be viewed as an intelligent and autonomous entity used on the basis of technological tools at the hands of education and learning, and we mean to teach what the teachers want in class? The term rational agent is a reference in ancient literature by which the whole world is viewed as an intelligence capable of perceiving the situations in a given place.

Technological autonomy should be taken seriously in educational settings when making decisions and processes. If we can design systems that can think and act autonomously without the need for human intervention (to change learning content or to provide feedback), then the system is autonomous; however, the decisions that we make are built and educated by human beings. This is where autonomy is functional, not ontological. The system is not in the least naïve and acts within parameter limits [5, p. 72-76]. Bostrom writes of the possibility to achieve systems with higher strategic autonomy, but the difference is that we talk about our systems (both in a derivative and conditioned sense) from more formal ideas of autonomy from being programmed.

The distinction between simulation and experience should be critical in education. Generative models can produce text describing emotional states, reactions, or subjective experiences, but cannot lead to phenomenal consciousness or understanding. Modern AI has no phenomenal consciousness nor real reflexive ability [10, p. 146-150], and it works as an information-processing system and not as a subject of experience or learning. Those systems, though with real-life effects are apparent in the education system which play an important role to students to assess learning and feedback. In this sense, AI should be viewed as a socio-technical infrastructure built into education. Given that AI's ontology is relational, its existence becomes meaningful, on the basis that its effects can be seen and observed in the learners and teachers who access it as well as in the institutional learning environment [5, p. 101–105].

Levels of intelligence in artificial systems

The intelligence of artificial systems in reality is usually defined differently in terms of functional and biological sense, and the systems must receive and process input information as well as output related to the goal. Artificial intelligence has not yet been viewed as the one thing but more as a continuum of computational tools as each level to the abstraction is further developed and capable to achieve.

The first level might be represented by rule-based systems (in which behavior is determined by explicitly programmed instructions). These are ruled via predefined logical structures and they can work well in traditional environments, but are not versatile in dealing with new and untested settings.

Finally, a second level is represented by machine learning systems in which performance is explicitly encoded but the underlying parameters of the model are learned from the data. Within machine learning, the models and their statistical model identify the regularities and in a few cases adapt the training parameters. It improves the flexibility of a model for operation in dynamic systems but as model complexity increases, it can be tough to interpret.

The third level is based upon deep learning and multi-layered representation as well as highly hierarchical feature extraction. These methods rapidly transform data into very clear and coherent internal representations, allowing the system to perform well with learning concepts and tasks; where a deep learning architecture will support the task: pattern recognition, with language recognition/loss extraction and decision making.

A fourth level is generative models that not only analyze or classify information but generate new bits. Such systems learn probabilistic distributions from large samples and produce outputs that are statistically consistent with learned information patterns. This goes from analytical systems to systems capable of producing information and therefore the same as if data is being trained.

Intelligence is viewed across these levels increasingly as something that evolution in a large-scale optimization process generates not something we wish to make to be intrinsic in our system or don’t expect it on every particular stage. Despite architecture- and performance-based differences, we know that all these systems are still essentially constructed on the basis of mathematical optimization and data-driven learning processes.

A key distinction in artificial intelligence research is with regard to representation and interpretation. Early systems were based on a formal representation, whereas the more contemporary ones are based on distributed and high-dimensional representations that are not directly understandable in humans. This is an ever-changing space, for which it has already created some transparency and explainability problems.

Lastly, it is important to mention that artificial intelligence systems differ significantly in their generalization beyond training. Some are constrained by particular training tasks and tasks which are hard to do in AI and some are flexible but have an ability to be applied beyond one domain. Still, we know that a generalization of AI systems would be constrained by the size of the training data we do not have, with or without those data needs, some of the objectives of our programs as we cannot perform the entire task.

However, artificial intelligence is a set of computational paradigms with different ways of learning, representation, and generalization that should not be considered as a single model of intelligence.

Table 2. Multi-Level Comparative Analysis between Biological Intelligence and Artificial Intelligence in Relation to Educational Processes

Dimension of Analysis	Symbolic paradigm	Connectionist paradigm	Generative paradigm
Ontology	Intelligence as symbolic manipulation	Intelligence as distributed process	Intelligence as probabilistic emergence
Epistemology	Deductive	Inductive	Predictive-probabilistic
Type of Representation	Explicit	Distributed representations	High-dimensional vector representations
Explanation / Prediction Ratio	Priority of explanation	Balance	Priority of prediction
Degree of Transparency	High	Medium	Low
Fundamental Limitation	Logical rigidity	Lack of explainability	Lack of causality
Educational Relevance	Rule-based instruction, structured curriculum, teacher-centered pedagogy	Adaptive learning, personalized instruction, learner-centered approaches	AI-generated content, automated tutoring systems, assistive learning technologies

Such a comparison suggests not to compare artificial intelligence with the model for replicating human intelligence for specific tasks, i.e., for the areas such as the areas of learning, instruction, and educational support [12, p. 37-40].

Artificial Intelligence and change in education process

In teaching, intelligent systems enable learner focus to tailor the materials to each individual student. Educational platforms can track student performance and adjust exercises to develop deficiencies in the learning mechanism, if needed [6, p. 3-6; 9, p. 438-440]. Digital changes are affecting the nature of education as well as the ways in which knowledge is made and distributed [2, p. 57-63]. Thus, data-based and adaptive learning spaces are emerging out of this space.

This adaptability may further enhance the efficiency of the education process, but it also raises risks. Assessment automation can make education less than objective with the loss of an individual's personal history and growth of critical thought [10, p. 154-158]. Given that technology has very effective implications on educational and organizational practice, the relevance and importance of AI (to our pedagogies) is clearly demonstrated by using AI reflexively and pedagogically from the beginning in the context of education [7, p. 9-12].

In addition, design-management of assignments/projects and learning tasks by generative systems can damage the authenticity of learning. Education remains an arena of reflexive development, motivated by cognitive effort, understanding, and meaning-making. Thus, technological technologies should be employed in the learning context in support of the teaching and learning rather than being ignored for cognitive and pedagogical roles [5, p. 101-105]. International works on AI ethics stress the importance of the human touch in these disciplines and this focus on education-centered and autonomous education should be the role of teachers and school management as to the role of digital technology development in education policy, to ensure that educational structures and institutions should be trained on it as well as education systems or as a way to inform their technology management from where learning and education in AI policy and ethics take place.

The ethical dimension and International Regulation

Education in the field of artificial intelligence requires the creation of clear normative and pedagogical frameworks. Transparency, fairness, and accountability in the field of education are critical for building trust in our education system and equality in access to learning opportunities [4, p. 11-16].

European regulations are in defense of robust principles of trustworthy artificial intelligence, based on respectful notions of fundamental rights; human accountability; and educational duty [4, p. 18-22]. On the other hand, UNESCO stresses the need to protect cultural diversity and reduce social inequality generated by digital technologies, especially in educational areas [14, p. 7–12]. The ethics of artificial intelligence should not be a set of external rules, but to be integrated into the design and implementation of educational technologies. It is responsibility that should be laid from the researchers, developers and educational institutes to the students and teachers for implementation with knowledge [5, p. 101-105]. The specialist literature presents systems of threats for school systems in the absence of these systems making it even more important to have a ready response at any age to the future threat to education because in our study [1, p. 191-197] and they need an active and proactive approach towards the development and use of intelligent education and technology because of the potential of such technologies in education for any human and a learning institution in advance. With knowledge and knowledge our system of systems can now control and so are intelligent technological things for its learning process as well as assessment and pedagogy [12, p. 103-105].

General conclusions

The current scientific accounts presented today about artificial intelligence do not constitute AI merely a data processing model, but is in fact an artificial cognitive tool and a way to remake contemporary epistemic and teaching practices in ways for learning and education. Artificial intelligence is not only a software or computer tool, but an epistemological process and ultimately the basis of learning for knowledge, teaching and knowledge making across different cultures.

The transformation of the symbolic paradigm into connectionist models and later into generative models is very profound. For the symbolic paradigm intelligence was an idea of the form of an explicit picture and learning and distribution (to a more general form) as a whole; in connectionist models a learning process is distributed out over discrete networks and the generativity model involves taking the probability distribution and learning from where the values are happening.

We believe it is the shift from explaining to predicting that causes change. Today's systems are mainly evaluated on their predictive performance and the goals related to the learning. This change also creates the epistemological conflict between correlation and causation to the point where its correctness is inoperable. We move more from knowledge to experience and learning and with that is an impact on evaluation and learning of learning.

From the human-centered perspective artificial intelligence should be thought of as something that evolved from something to be learnt from, rather than as an autonomous object in phenomenological. System autonomy is built purely from algorithms and human decisions, and is therefore influenced by human-designed objectives. It does not imply language representation or de-facto awareness about being the same (we can all experience or have) reflexive consciousness in an environment of learning that there is no reality/action in which we can think. So this distinction is very significant when it comes to understanding the role of AI in education and teaching.

We can compare artificial and biological intelligence efficiently and find out that they both have functional parallels but are fundamentally different in terms of ontologies. Artificial neural networks represent mathematical simplifications of biological processes and computational methods are hierarchically organized. But we would not have the plasticity and metacognition or the subjective experience we encounter as a human in our brains. This distinction is now particularly critical in education where meaning and reflection are at the heart of it.

In the field of education technology, artificial intelligence has great potential for teaching and learning in the field of personalization, feedback automation, and training based on learning, that is where artificial intelligence can be key. However, the fact is the distribution of responsibility will be still a matter that is very much to be worked out and is done by teaching, ethics and human skills. The teacher is critical for driving and proving the education pathway.

In conclusion, all artificial intelligence to date has not only had this kind of instrumental intelligence, it needs to be understood in terms of how those tools are constructed and why they form and as a kind of statistical mechanism that is less of an exact replication of human capabilities. AI is the future of education and has its own limitations in terms of its job, but to the degree there have to be a balance of technological innovation with ethical consciousness about teaching and learning and human respect for learning at its core and learning skills can't exist alone. With AI we are going to be able to more understand intelligent systems better in class and so on so much more, and we want people to come to understand who we are in school about with such intelligent systems and what is the rationale for us to know and in what direction and with how we would teach it?

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