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The conditions and results of innovation in educational models

Applications of Artificial Intelligence to higher education: possibilities, evidence, and challenges

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Abstract

The range of applications of artificial intelligence (AI) to education is increasing ceaselessly, although its generalization still seems far away. Despite the enormous opportunities that AI can offer to support teaching and learning, the development of applications for higher education carries numerous implications and also ethical risks. Against this context, this contribution aims to offer a review of AI applications in higher education, taking as a starting point the heritage of research developed in the last two decades. It explores the definitions of AI in education and the elements and methods that AI applications could bring to higher education, discussing the challenges that emerge and finally suggesting some conclusions.

Sintesi

La varietà delle applicazioni dell'intelligenza artificiale (AI) all'educazione sta aumentando continuamente, sebbene la sua diffusione generalizzata sembri ancora lontana. Nonostante le eccezionali opportunità che l'AI può offrire in favore di insegnamento e apprendimento, la sua applicazione nell'istruzione superiore ha numerose implicazioni e anche rischi etici. Su questo sfondo, il presente contributo ha l'obiettivo di presentare una rassegna delle applicazioni dell'AI nell'istruzione superiore, partendo dalle ricerche sviluppate negli ultimi due decenni. Si esplorano le definizioni di AI in ambito educativo, gli elementi e i metodi che le applicazioni dell'AI possono apportare all'istruzione superiore, discutendo le sfide che ne emergono e suggerendo, infine, alcune conclusioni.

Keywords: artificial intelligence, higher education, innovation, educational technology

Parole chiave: intelligenza artificiale, istruzione superiore, innovazione, tecnologia educativa

Introduction

The range of applications of artificial intelligence (AI) to education is increasing ceaselessly, although its generalization still seems far away (Popenici & Kerr, 2017). Despite the enormous opportunities that AI can offer to support teaching and learning, the development of applications for higher education carries numerous implications and also ethical risks. For example, in times of post-crisis budget cuts, administrators may be tempted to replace teaching with cost-effective automated AI solutions. Faculty members, teaching assistants, educational advisors, and administrative staff may fear that intelligent tutors, expert systems, and chat robots will take their jobs away from them, perhaps not without reason. The application of AI, in particular to learning analytics, requires vast amounts of data, including confidential information about students and teachers, which raises serious privacy and data protection issues.

Against this context, this contribution aims to offer a review of AI applications in higher education, taking as a starting point the heritage of research developed in the last two decades. It explores the definitions of AI in education and the elements and methods that AI applications could bring to higher education, discussing the challenges that emerge and finally suggesting some conclusions.

1. AI in education: origins and recent developments

The birth of AI dates back to 1956 when John McCarthy organized a two-month workshop at Dartmouth College in the United States. In the workshop proposal, McCarthy first used the term artificial intelligence (Russell & Norvig, 2010). To him comes the conjecture that every aspect of learning or any other intelligence feature can be described so precisely that a machine can be designed to simulate it. Therefore, it would be a matter of finding ways to make machines use language, form abstractions and concepts, and solve the kinds of problems now reserved for humans and improve themselves. On this basis, Baker and Smith (Baker, Smith, & Anissa, 2019) offer a broad definition of AI as computers that perform cognitive tasks generally associated with human minds, in particular learning and problem-solving. Thus, AI does not refer to a single technology but is used as an umbrella term that describes a wide range of technologies and methods, such as machine learning, natural language processing, data mining, neural networks, or a variety of algorithms.

The field of AI has its origins in computer science and engineering but is heavily influenced by other disciplines. There is little agreement among AI researchers about a possible standard definition and understanding of AI - and intelligence in general. In the specific field of higher education, the truth is that many professors do not know its scope and, above all, what it consists of (Vinuesa et al., 2020).

AI and machine learning are often mentioned as equivalent, but they are not. Machine learning is an AI method for grading and profiling, supervised and unsupervised, predicting how likely a student is of dropping out of a course or joining a program, or identifying problems in written assignments. In this sense, machine learning has been defined as a subfield of artificial intelligence that includes software capable of recognizing patterns, making predictions, and applying the newly discovered patterns to situations that were not included or covered by its initial design (Popenici & Kerr, 2017).

It is often difficult to distinguish clearly between learning analytics (LA) and AI in education. An important reason for this is that evidence of LA's actual application, and its effect is only available in a very fragmented way (Renz, Krishnaraja, & Gronau, 2020). The most common definition of LA is the measurement, collection, analysis, and reporting of data about students and their contexts, to understand and optimize learning and the environments in which learning occurs (Phil & George, 2011). In this way, LA is also considered the process of developing actionable knowledge through the definition of problems and the application of statistical modulations and analyses against existing or future simulated data, [allowing] institutions to experiment with the data to gain knowledge, improve the student learning experience and student outcomes, and identify improvements in the efficiency and effectiveness of delivery. Therefore, LA is only one promising component of AI in education.

Another fundamental concept for AI is that of rational agents. An agent is an element that perceives its environment through sensors and, after processing the information received rationally, acts on that environment through actuators (Russell & Norvig, 2010). The vacuum robot is a simple form of intelligent agent, but things become more complex and open when we think of an automated vehicle.

Learning analytics is a powerful resource for making informed decisions and achieving better learning outcomes. Learning analytics draws on the availability of large amounts of data that can be scrutinized to extract knowledge or develop intelligent tools useful for educational or administrative tasks. Nevertheless, analyzing and making the most of the data is not an easy task. Advanced data mining techniques are used to do this, which in turn rely on other fields such as *big data* technologies to handle large volumes of data, self-learning algorithms that learn from the data, and visualization tools for efficient communication with the people whose decisions are meant to help inform.

All these layers of software for intelligent data processing allow to obtain knowledge, detect learning patterns, predict future situations, or give recommendations to optimize the available resources. Analytics is also a crucial step in the development of future AI solutions that, with the help of powerful libraries, including natural language recognition, language translation, and game theory, will allow, for example, to create avatars that simulate the behavior of a virtual teacher for students or a teacher's assistant. The bright prospects for the future make it possible to anticipate an AI ecosystem that can help overcome the various challenges linked to higher education quality and equity, particularly when it is offered in hybrid or fully distance mode. While the future of AI solutions is auspicious in the medium term, current solutions focus on making the most of data mining and analysis technologies.

2. Possible areas of application

There seems to be a growing, shared understanding of the advantages of using AI in learning environments are: a) to increase students' learning (experiences and effectiveness) and their motivation for learning, and therefore reduce student drop-out or inactivity and increase completion of studies; and b) to provide customized and adaptable learning paths through specific objectives set by the teacher or student to support the learning process. However, the use of AI outside Australia, the UK, and the USA is still relatively rare (Ifenthaler & Yau, 2019).

2.1. A global perspective

The student's higher education experience can be seen as a series of interdependent, overlapping, but not necessarily sequential phases (Kriti Khare, Stewart, & Khare, 2018). This life cycle approach is often used by administrators to manage students' lives, as it distinguishes the critical elements of the experience that enable the design and delivery of focused administrative services. The student life cycle in higher education is defined as the student's journey from first contact with an institution to becoming an alumnus. A student's ultimate goal is academic achievement accompanied by personal development through academic experience. The academic success of students, however, depends on a composite of all aspects of the student's life. These other aspects include mental well-being and support, social interactions, sports and physical health, and life balance, all of which contribute to the student's higher education career experience (Morgan, 2013). At least in theory, there is no area of activity at an institution of higher education in which AI cannot potentially have a noticeable impact (Zeide, 2019).

First, there is the institutional use. Universities, particularly those engaged entirely in distance education, are increasingly dependent on algorithms for marketing to prospective students, estimating class size, planning curriculum, and allocating resources such as financial aid and facilities. This leads to another application of AI, student support, which is increasingly used in higher education institutions. Schools use machine learning in student orientation. Some applications help students to schedule the loading of their courses automatically. Others recommend courses, majors, and career paths, as guidance counselors or career service offices traditionally do. These tools propose recommendations drawing on how students with similar data profiles performed in the past.

Another area for the use of AI in supporting students is "just in time" financial aid. Institutions of higher education can use student data to provide students with microloans or last-minute advances if they need financial assistance to, for example, make it to the end of the semester and not drop out. One of the most prominent ways in which predictive analysis is being used in student support is in early warning systems, analyzing a wide range of data – academic, non-academic, operational – to identify students who are at risk of failure or drop-out, or who have mental health problems. This use shows some of the real potentials of artificial intelligence – large data can give editors a more holistic view of the student's situation.

Finally, universities can apply artificial intelligence to improve teaching and learning processes. This involves creating systems that respond to the pace and progress of individual users. Educational software evaluates student progress and recommends specific parts of a course for students to revisit or additional resources to consult. These are often referred to as custom learning platforms.

These efficiencies are expected to lead to greater effectiveness, effective teaching, learning, institutional decisions, and guidance. So this is yet another promise of AI: that it will show educators things that they cannot assess or even imagine given the limitations of human cognition and the difficulty of dealing with many different variables and a wide range of learners.

Alternatively, it is also possible to classify the uses of AI in higher education, according to the end-user (Baker et al., 2019), i.e.:

(a) the student;

(b) the teacher; and

(c) the AI system itself.

Student-oriented AI tools are computer applications that students use to learn a subject, i.e., adaptive or personalized learning management systems. Teacher-oriented systems are used to support the teacher and reduce his/her workload by automating tasks such as administration, assessment, feedback, or plagiarism detection. AI tools also provide information about students' learning progress so that the teacher can proactively offer support and guidance when needed. System-oriented applications are tools that provide information to administrators and managers at the institutional level to facilitate their decision-making processes based on evidence of student behavior, courses and programs.

2.2. The advantages for instruction

More specifically, in the case of instruction, there seems to be some consensus about three broad categories of AI applications in education that are already available today (Luckin, Holmes, Griffiths, & Forcier, 2016), such as personalized tutors, intelligent support for collaborative learning; and intelligent virtual reality.

Intelligent Tutoring Systems (ITS) can be used to simulate custom tutoring. Based on learning models, algorithms, and neural networks, they can make decisions about a particular student's learning path and the content to be selected, provide cognitive scaffolding and assistance, involving the student himself in the dialogue. ITS has enormous potential, especially in large-scale distance higher education institutions, which offer modules with thousands of students, where personalized human tutoring is impossible beyond relatively frequent individualized attention, solely for economic reasons. A wide range of research shows that learning is a social exercise: interaction and collaboration are at the heart of the learning process (Jonassen, Davidson, Collins, Campbell, & Haag, 1995). However, online collaboration does not just happen. It must be facilitated and regulated (Salmon, 2003). AI can contribute to collaborative learning by supporting the formation of adaptive groups, by facilitating online group interaction, or by summarizing discussions that can be used by a human tutor to guide students toward course goals and objectives.

Finally, intelligent virtual reality can be used to engage and guide students in virtual reality environments. Virtual agents can pretend to act as teachers, facilitators, or student peers, for example, in virtual or remote laboratories (Perez et al., 2017). With the advancement of AI and the availability of large volumes of student data whose analysis can be crucial for analyzing learning and improving it, there is no doubt that a renaissance of assessment is taking place (Luckin et al., 2016). AI can instantly provide feedback and assessment at the precise moment when this information may be critical to the teacher, the student, or both. Instead of assessment being a specific activity, to which time and effort must be devoted, AI can be incorporated into learning activities for ongoing analysis of student achievement, from the perspective of what has traditionally been called formative assessment. Thus, for example, algorithms have been used to predict that a student will fail a task or drop out of a course with high accuracy with predictive success scores ranging from 75 to 95% (Bahadir, 2016).

3. The contributions of empirical research

To what extent have these theoretical possibilities given rise to empirical research? A recent review of research on the applications of AI to higher education (Richter, Juarros, Bond, & Gouverneur, 2019) has shown that, in reality, leaving aside the theoretical possibilities, it is possible to group everything that has been developed so far around four main areas:

(a) adaptive systems and personalization;

(b) monitoring and evaluation;

(c) profiling and forecasting; and

(d) intelligent tutoring systems.

The following table shows the percentage of studies dedicated to each area.

Area	Percentage
Profiling and forecasting (admission decisions and course scheduling; drop-out and retention; student models and academic achievement)	39%
Intelligent tutoring systems (teaching course content; diagnosing strengths and automated feedback; preserving learning materials; facilitating collaboration; the teacher's perspective)	19%
Evaluation and assessment (automated grading; feedback; assessment of student understanding, commitment and academic integrity; teaching evaluation)	24%
Adaptation and customization systems (teaching course content; recommending customized content; supporting teachers and learning design; using academic data to monitor and guide students; representing knowledge in concept maps)	18%
Total	100%

TABLE 1 - APPLICATIONS OF AI TO HIGHER EDUCATION (ADAPTED FROM RICHTER ET AL., 2019)

3.1. Profile and prediction

The basis for many applications of AI are models or profiles of learners that can predict, for example, the likelihood of a student dropping out of a course or being admitted to a program, in order to provide timely support or provide feedback and guidance on content-related issues throughout the learning cycle. Analysis, modeling, and prediction are an essential part of data mining in education (Krishna, Kumar, & Sri, 2018). Accurate prediction of student performance can be critical to making admissions decisions and providing better educational services (Chen & Do, 2014). In general, research shows that admissions decisions can be predicted with a high level of accuracy, so an AI solution could relieve administrative staff and allow them to focus on the more complicated cases. On the other hand, studies on drop-out and retention aim to develop early warning systems to detect students at risk in their first year or to predict the attrition of university students in general). Many other studies are concerned with profiling students and modeling learning behavior to predict their academic achievement at course level.

3.2. Intelligent tutoring systems

Research on student profiles is an essential basis for intelligent tutoring systems and adaptive learning environments. More research is thus needed on the effectiveness of these systems. One of the most relevant meta-analysis in this particular areas was published over 5 years ago: Steenbergen-

Hu and Cooper (Saiying Steenbergen-Hu & Harris Cooper, 2014) found that ITS had a moderate effect on student learning and was less effective than human tutoring; but it outperformed all other methods of instruction (such as face-to-face instruction, reading printed or digital text, or homework assignment).

In general, these ITSs focus on providing learning content to students while supporting them by giving adaptive feedback and clues to solve content-related questions and detecting students' difficulties/errors in carrying out the proposed activities. Other possibilities, although with little empirical research, are:

- diagnosing the strengths or gaps in students' knowledge, and providing automated feedback;
- the organization and presentation of learning materials based on the needs of the students;
- facilitating collaboration between students;
- the maximization of the teaching effort, with the aim of reducing the teacher's workload.

Despite its enormous relevance, this is an area with hardly any empirical research. Monitoring discussion forums provides another opportunity to improve the effectiveness of collaborative forums. Teaching assistants (humans) are currently asked to check the forum at least once a day so that all questions can be answered within 24 hours. The same rules apply to e-mails, and intelligent tutors are encouraged to ask students to post a question on the forum if their answer would be useful to other students. By associating a set of resources with each topic, it is possible to point out these resources to students, just as a teaching assistant would have done (K. Khare & Lam, 2018). The algorithms can be used to time the student response, and if a response is not found or takes too long, a mechanism can be put in place to notify a teaching assistant. Once the assistant solves the question, the algorithm can be trained further to answer the next time or to mark specific questions that should go to the assistant directly. Going beyond answering the questions, reviewing the forum messages for student understanding, using content analysis and text mining techniques can determine whether the coverage of the discussion is as expected. Several studies (S. Steenbergen-Hu & H. Cooper, 2014) have indicated that intelligent tutors may be as good or better than human tutors; however, the evidence is not clear, and the experimental designs used to date do not provide an unequivocal answer.

3.3. Monitoring and evaluation

In general, studies show that AI applications can perform evaluation and assessment tasks with very high levels of accuracy and efficiency. However, because of the need for human supervision, they are more applicable to courses or programs with large numbers of students. Interestingly, however, it has been found that the benefits of using algorithms that find patterns in student responses lead to increased requests for review of assessments and a move away from merely measuring student knowledge and skills through multiple-choice tests.

Automated assessments are mostly direct tabulations of multiple-choice questions, where there is a predetermined correct answer. Assessments and scoring of less discrete answer sets, particularly long essay questions, are not likely to be received as warmly by academics. However, AI is being applied to the grading of both short and long essay types and shows considerable success. Work in this area includes automatic feedback. Automatic scoring of short-answer questions has been much studied (Zhang, Shah, & Chi, 2016), but automatic essay scoring is a still-growing field of research aimed at scoring long essay questions. Chen, Breslow, and DeBoer (X. Chen, Breslow, & DeBoer, 2018) analyzed a mixed learning environment and the effects of immediate corrective feedback on student behavior. They found that the feedback led to a reflective study, and higher performance was predicted for students who used the corrective feedback function. Fruitful research on feedback examines a battery of student tools, such as intelligent agents that provide students with cues or guidance when they are confused or stuck in their work, and automatic learning techniques to generate automatic feedback and help improve student writing.

3.4. Adaptation and customization systems

This area refers to adaptive systems that offer content, materials, and exercises customized according to the students' behavioral profile. In this sense, they can support teachers in the design of learning and teaching by focusing on extracting academic information from students to perform diagnostic tasks and help teachers to provide more proactive personal guidance or, in addition to that task, facilitate performance assessment and personalized assistance and feedback.

Adaptive learning has been much touted over the years and was considered one of the first benefits of online or computer-based learning. In adaptive learning, a program can judge when a new topic needs to be introduced, or an older topic needs to be revisited by the student. The models used by intelligent tutoring systems could be useful here to determine when a student has effectively learned a concept and is ready to move on to the next (Lin & Chi, 2016). Task data and practice questions, as well as response time, are often used to find the "learned" state and build a student model that represents the students' knowledge. These systems provide feedback, just-in-time guidance, and explanations when students make mistakes. They track learning outcomes and can determine content appropriate to the student's level of difficulty (VanLehn, 2006). In this way, the students' learning experience is more focused on the most appropriate lessons. The use of games in education draws on a similar pedagogical approach of discovering within a dependent and interrelated environment objects or situations of knowledge. Polin (Polin, 2018) explains the characteristics of games that make them learning support spaces. Lamb, Annetta, Firestone, and Etopio ((Lamb, Annetta, Firestone, & Etopio, 2018) provide information on the type of games – Serious Games, Serious Educational Games and Educational Simulations – that have the most significant impact on student cognition and behavior.

4. The challenges

Given the possibilities offered, at least theoretically, by AI in higher education, and having also examined the areas in which empirical research has made progress, it remains to identify the fundamental challenges that would have to be faced in order for these possibilities to materialize.

4.1. Teaching staff

There are no indications that the adoption of artificial intelligence-based applications is beginning to become widespread in higher education, at least for the time being, although the educational technology industry has not yet ceased to produce new developments. Their fundamental flaw is that instead of addressing the problems and issues that teachers face daily, they promote new ways of organizing teaching that clash with dominant traditional practices, often without rigorous evaluations to support the supposed benefits of the new solutions. Not surprisingly, teachers listen to what vendors have to say, but they do not necessarily accept everything proposed to them. In this context, some countries have already designed policies that support the efforts of the domestic educational technology industry to promote innovation, to intensify efforts and modalities of qualification and empowerment of teacher demand, while supporting their innovative practices and, finally, to explore how AI can contribute to a more vibrant and more evidence-based higher education learning environment.

Platforms that support learning analytics can use predictive algorithms to help teachers diagnose and anticipate the learning difficulties faced by students and thus implement customized interventions to respond to those difficulties. While predictive algorithms facilitate data analysis and interpretation, these algorithms are not what make learning analytics systems powerful. Their effectiveness lies in their usefulness and relevance for students and their teachers. Real-time data processing should result in real-time feedback, enabling faster pedagogical intervention and individualized instruction. Teachers must continue to play the leading role. Managers and teachers must have sufficient autonomy to manage their respective institutions and courses based on the principle that they are more familiar with their students' needs. Automated testing only serves this autonomy if faculty and administrators are empowered to manage the delivery of educational services in their respective institutions. Otherwise, the application of any AI-driven tool can only lead to confusion and contradictory, if not outright negative, results.

Therefore, teachers will remain on the frontline of higher education: those who say that AI can replace teachers are misinformed. The arguments they make reduce university teaching to the performance of exclusively cognitive and routine tasks, ignore research that underlines the importance of a human tutor to support the learning process, and neglect the creative and socio-emotional aspects of training, which go beyond the mere transmission of knowledge (Bali, 2017). Furthermore, university professors will always decide how and when it would be appropriate to use the tools supported by AI using their proverbial autonomy. The development of these AI-supported tools and their integration into higher education programs should be a participatory process, designed to "provide the support that teachers need – not the support that technologists or designers think they need" (Luckin et al., 2016). That said, AI-enabled technologies offer opportunities to automate particular routine and administrative tasks, such as classification and record-keeping, that teachers are currently performing. Automation of such tasks can free up teachers' time, allowing them to devote more energy to the creative, empathetic, and inspirational aspects of the academic profession.

For an eventual generalization of the use of AI in higher education institutions, teacher training is a key aspect in enabling teachers to use educational data to improve their teaching strategies and methodologies. To be able to use AI-supported technologies effectively, teachers would also need to assimilate new skills, specifically:

- a clear understanding of how AI-supported systems can facilitate learning can make sound value judgments about new products and solutions offered to them;
- research and data analysis skills can interpret the data provided by AI-based systems, interrogate data, and provide students with feedback drawing on the perceptions that emerge from the data;
- new management skills to effectively manage the human and artificial intelligence resources at their disposal;
- a critical perspective on the ways AI and digital technologies affect human lives and new frameworks of computer thinking and digital skills for students to understand the power, dangers, and possibilities of AI.

Teacher education programs in higher education institutions should, therefore, take account of these new skills. However, not only teachers have to be prepared to understand and comprehend the new technological possibilities that digital and AI education are unfolding. The history of innovations in education depicts a lost land of promises because of a lack of understanding of the prevailing pedagogical culture and how teachers work in universities. To design new educational possibilities, AI developers have to dialogue with teachers, content designers, and interdisciplinary specialists.

There are currently two distinct communities of researchers, namely those focusing on learning analytics (LA) and educational data mining (EDM). These two communities overlap in terms of objectives and techniques but differ in the extent to which the MDE researchers, coming from the intelligent tutoring community, work on cognition at a tiny scale. MDE methods are drawn from various disciplines, including data mining, machine learning, psychometrics and statistics, information visualization, and computer modeling. The field of learning analytics focuses more on learning content management systems and their relationship to academic achievement. It does this by combining institutional data, statistical analysis, and predictive modeling to identify which students need help and how teachers can intervene to improve academic achievement.

4.2. Meaningful research for teaching

While it is reasonable to expect an increase in research on the application of AI in higher education in the coming years, it is also worth recalling the difficulties the sector faces to take stock of educational research in a meaningful way for practice and policymaking. The particular field of educational technology research clearly demonstrates that what researchers declare as key research issues is often not related to teachers' actual needs. The potential of technology to transform education has often been affirmed, although it is widely accepted that, for various reasons, this potential has not yet been realized as expected. In examining how decisions are made about the use of technology in education, it is shocking to realize how little is known about the effects of technology on the quality of university education and, more specifically, what particular uses of technology can lead to improved learning. The current development of AI in education seems to be another example of this well-known phenomenon. This situation is far from optimal in the most impoverished and most resource-constrained developing contexts, where technology-based reforms are being promoted as a remedy for poor economic and social conditions. Since many national initiatives in this context often emphasize the provision of access to technology as intrinsic value-added, as shown during the COVID-19 crisis, there has not been much research on the actual impact on learning.

It is commonly said that the adoption of an innovation depends essentially on the perception by the end-users of the benefits of implementing a new strategy in relation to what they are currently using. Applying this principle to the specific case of technology in higher education, it can be expected that AI supports the design of new strategies to engage students:

- learn better, for example, in a more personalized way;
- learn more, i.e., get better learning outcomes; and
- learn different things, that is, achieve learning goals that only technology can allow.

Research should identify the strategies that make this possible and, ultimately, the conditions under which these strategies could be generalized. The question of feasibility is essential for learning because there may be many strategies that could be incompatible with the current configuration of universities and even the teaching profession.

Educational research, related to technology and in general, is a complicated task because of the very nature of education and because contextual conditions limit its ability to provide results from which generalizations can be drawn, thus affecting its capacity to contribute to the creation of universally valid theories. In education, there is a pervasive problem of these so-called "ubiquitous interactions"; that is, the large number of variables that are inter-related and increase the difficulty of isolating impacts or combining the results of different studies. Since it is complicated to isolate the influence of strategies, the socio-economic context, motivation, and interaction between all these variables make it very difficult to arrive at universal recipes. As there are no universal solutions, it is imperative that research also has a local dimension, in each university's classrooms, recognizing professors and students as actors and not as mere beneficiaries or users of previously packaged technological solutions. There is no doubt that research has a role to play in elucidating the role that technological solutions play in improving the quality of university education. However, the right research questions need to be asked. Since educational phenomena are quite complex and multifaceted, the right questions do not concern the use or non-use of AI in higher education, in absolute terms, but which AI solutions can best be adapted to the evolving teaching and learning needs of each teacher and student given their closer reality. The potential of AI in higher education may seem very promising, but unless it is appropriately integrated into everyday teaching and learning practices, its educational effects will never become visible.

4.3. Ethics and transparency in the collection, use, and dissemination of data

The ethical dilemmas that arise in the large-scale collection, production, analysis, and dissemination of data on people are another important consideration when addressing AI's potential. However, it should be noted that trying to understand the ethical implications of new technologies is by no means a new goal. Over the past three decades or so, academics and practitioners have sought to define some form of information ethics that can be summarized in one question: What should an ethical use of technology look like? The emergence of data science has shifted the discourse from information ethics to data ethics. Experts have advanced the notion that "it is not the hardware that causes ethical problems ... it is what the hardware does with the software and the data that represents the source of our new difficulties" (Mittelstadt, Allo, Taddeo, Wachter, & Floridi, 2016).

How do these general concerns translate into the specific field of AI applications in higher education? Probably around issues like the following.

- Access to higher education. More and more educational institutions are using automatic learning algorithms to accept or reject students. Two potential problems that arise are: (1) Lack of transparency. Some programs cannot easily explain why particular students are accepted while others are rejected. Should every student have the right to understand those reasons? (2) Unfair discrimination. When machine learning algorithms are trained with a specific data set (say with students from a Western European country), the result may not be directly applicable to students from other parts of the world. The initial database could be biased towards a particular group and therefore discriminate unfairly when used in a different group.
- Recommendations to individual students. If the recommendations are the result of automated learning based on a large data set, the resulting recommendation may not be suitable for students from a different target group. If the recommendations are based on the individual student's learning history, then this problem no longer exists.
- Concentration of personal data. If – as in the digital world – educational platforms are owned by a few major worldwide players, two concerns arise: (1) the concentration of personal information (of students and teachers), which could create a risk to privacy. Large amounts of personal data are an attractive target for cybercriminals; (2) dominant platforms could forge data monopolies by monopolizing the market on the ability to develop the best algorithms. This would give them great power and increase concerns about the lack of transparency in making decisions about individual students' learning paths.

- Accountability – What if the automated decisions that guide students in their learning process turn out to be wrong? Who or what is ultimately responsible and accountable? The owner of the platform? The assigned teacher? The algorithm?
- Impact on the job. If AI systems increasingly automate tasks that teachers usually perform, what will happen to their work? AI systems can assess the student's initial competency level, guide her through the different stages of the course, applying collective intelligence combined with individual experience, automatically evaluate test results, and even simulate, to some extent, student-teacher interaction.

Data privacy and security arise almost immediately in debates about data ethics (Zeide, 2019). The main challenge is to be able to use personal data while ensuring that individuals' personally identifiable information and privacy preferences are protected. Installing the necessary safeguards to prevent data theft is also critical. While the growth of regulatory frameworks at global, regional, and national levels on the protection of personal data certainly demonstrates a growing understanding of the urgency of the issue, many of these frameworks still do not provide adequate protection to citizens, both in policy and in practice.

Conclusions

Applications of AI to education have, from the beginning, faced many difficulties in growing because education systems around the world are, by their very nature, resistant to technological change. For several decades, AI has been part of a vision that promises to transform education by creating tutorial systems that help to personalize learning. This promise is beginning to unfold as today's technology is being experimented with different models around the world, raising many questions for education in general and higher education. The lack of longitudinal studies and, on the contrary, the overwhelming presence of descriptive and experimental studies from the technological point of view, as well as the prevalence of quantitative methods – especially the quasi-experimental ones – in the empirical studies (Richter et al., 2019) shows that there is still substantial scope for educators and university teachers themselves, whatever their discipline, to bring their perspective that could have a great impact on higher education, for example, by adopting approaches such as design-oriented research (Easterday, Rees Lewis, & Gerber, 2018). A recent systematic review of the literature on personalization in education through technology also unveiled the predominance of proposals that often used quantitative methods (Bartolomé, Castañeda, & Adell, 2018). It has also been noted that there are very few application studies and impact studies in learning achievement (Misiejuk & Wasson, 2017).

The overall consequences of AI application development in higher education cannot yet be clearly anticipated, but it seems very likely that they will remain a significant issue in the next twenty years. The applications developed so far offer enormous pedagogical opportunities for intelligent student support systems and support student learning in personalized and adaptive learning environments. This applies, in particular, to open and distance learning universities, where AI could help to overcome the issue of providing access to higher education to an ever-increasing number of students. On the other hand, it could also help them to offer flexible, interactive, and personalized learning opportunities, for example, by relieving teachers of repetitive tasks such as grading large numbers of assignments, so that they can focus on human accompaniment with learning empathy.

It is crucial to emphasize that educational technology is not just a matter of technology – the real concerns must focus on the pedagogical, ethical, social, cultural, and economic dimensions of AI. The danger, of course, lies in viewing data and coding as an absolute, rather than a relative, source of guidance and support (Selwyn, 2016). Education is too complex to be reduced solely to data analysis and algorithms. As is the case with digital technologies in general, data alone do not offer a clear technical solution to the dilemmas of education, no matter how shocking the results of the analysis of large masses of data may be. In China, systems are currently being used to monitor students' participation and expressions by recognizing their faces in the classroom (the so-called Intelligent Campus Classroom Behavior Management System) and showing them to the teacher on a tablet. This is an example of educational monitoring, and it is highly questionable whether such systems provide real added value to a good teacher, who should be able to capture the dynamics in a learning group (online and in a campus environment) and respond to their needs in an empathetic and pedagogically meaningful way, as a result of his or her expert professional judgment. Therefore, it is crucial to adopt an ethical perspective to start thinking about how the potential of algorithmic decision-making systems incorporated in AI applications is being explored (Prinsloo, 2017). Besides, we must always remember that AI systems, above all, require the control of humans over whose understanding of the problems and their alternative solutions the AI applications are programmed (Kaplan & Haenlein, 2019). Some critical voices remind us that we must go beyond tools, and talk again about pedagogy, as well as recognize the relevance of the human aspects of the use of digital technology in education (Castañeda & Selwyn, 2018).

A recent UNESCO report on the challenges and opportunities of AI for sustainable development deals with various areas that have important pedagogical, social and ethical dimensions, for example, ensuring inclusion and equity in AI, preparing teachers who will be decisive in the development of AI applications in education, setting up quality and inclusive data systems, or ethics and transparency in the collection, use and dissemination of data (Pedró, Subosa, Rivas, & Valverde, 2019). There remains a dramatic lack of critical reflection on the pedagogical and ethical implications and the risks of applying AI applications in higher education. Privacy issues are rarely addressed in empirical research on AI applications to higher education, as if they were not with them, as a recent systematic review on the topic of learning analytics has shown (Misiejuk & Wasson, 2017)).

More research is needed by teachers and instructional designers on how to integrate AI applications throughout the student life cycle to take advantage of the enormous opportunities they offer to create intelligent learning and teaching systems. The limited presence of AI researchers in university education departments is evidence of the need for educational perspectives on these technological developments. The lack of theory could be a widespread syndrome in the field of educational technology in general. A recent study has shown that over 40% of articles in three leading educational technology journals were entirely a-theoretical (Hew, Lan, Tang, Jia, & Lo, 2019), in line with other previous studies (Bartolomé et al., 2018). Most of the research focuses merely on analyzing and searching for patterns in the data to develop models, make predictions that inform students and teachers facing applications, or support management decisions using mathematical theories and learning methods developed decades ago (Russell & Norvig, 2010). This type of research is now possible thanks to the growth of computing power and the full availability of large digital student data. Nevertheless, there is very little evidence for the advancement of pedagogical and psychological theories of learning related to AI-driven educational technology. Researchers should, therefore, be encouraged to be explicit about the theories underlying empirical studies on the development and implementation of AI projects in order to broaden research at a broader level, helping to facilitate understanding of the reasons for and mechanisms of this dynamic development that is set to have a growing impact on higher education institutions worldwide.

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