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Opportunities and Challenges of Big Data and Artificial Intelligence for Entrepreneurship Education

Abstract: The main objective of this article is to identify and discuss the opportunities and challenges related to the development and use of Big Data and Artificial Intelligence in teaching and educating students in entrepreneurship. We also propose a research agenda to guide future work in relation to the many questions raised by the implementation of these new technologies in the field of entrepreneurship education.

Keywords: Education; Entrepreneurship; AI; Big Data; Research; Social Construction.

Opportunités et défis du Big Data et de l'intelligence artificielle pour l'éducation à l'entrepreneuriat

Résumé : L'objectif principal de cet article est d'identifier et de discuter des opportunités et des défis liés au développement et à l'utilisation du Big Data et de l'Intelligence Artificielle (IA) dans l'enseignement et la formation des étudiants en entrepreneuriat. L'article propose également un agenda de recherche pour guider les futurs travaux sur les nombreuses questions soulevées par la mise en œuvre de ces nouvelles technologies dans le domaine de l'éducation à l'entrepreneuriat.

Mots-Clés : Enseignement ; Entrepreneuriat ; IA ; Big Data ; recherche ; Construction sociale.

Introduction

The digitalization of economic activities and the introduction of new advanced technologies designed to create, store and analyze data are contributing to profound transformations in individual and collective uses, practices, value chains and behaviours (Phan et al. 2017).

The effects of the digital revolution and, more particularly, the consequences of Big Data and the rise of artificial intelligence on work, human productivity, innovation and management are the subject of reflection and emerging debate within management research communities (George et al. 2014; Nambisan et al. 2017; Phan et al. 2017; Toutain et al., 2023; Mohamed et al., 2024; Strzelecki, 2024).

Entrepreneurship researchers are also, of course, interested in these digital mutations/transformations and are examining the impact of digital technologies in general terms (Nambisan 2016) or by focusing on the entrepreneurial process in particular sectors (von Briel et al. 2017). Work is also being carried out on the links between Big Data and ecological sustainable entrepreneurship (Zeng 2017), entrepreneurial social networks (Wang et al. 2017) and entrepreneurial culture (Obschonka 2017).

However, even if some research has tried to study how and with what effects digital technologies (use of the Internet, social networks, smartphones in classrooms; mobilization of MOOCs based on transmissive or constructivist pedagogy; use of simulation or game software; development of distance learning or blended learning) are being implemented in the field of entrepreneurship education, it is clear that very few projects clearly linking Big Data, Artificial Intelligence and entrepreneurship education[1] are currently available. In the absence of scientific literature, there are issues and challenges that remain unexplored, while the processes of digital transformation are accelerating in all fields, including education (Eynon 2013; Daniel 2015; Cavanaugh et al. 2016).

Entrepreneurship education is already facing a series of epistemological, axiological, theoretical and pedagogical challenges (Fayolle 2013; Kÿro 2015; Fayolle et al. 2016). The rapid development of digital technologies and the technological disruption associated with the progressive implementation of advanced technologies such as Big Data and Artificial Intelligence will profoundly affect entrepreneurship education practices and research, generating new opportunities, but also new challenges. Moreover, the introduction of these technologies is likely to ask questions of higher education institutions, particularly with regard to the appropriation of these technologies and their use alongside traditional or innovative teaching methods (Boyd and Crawford 2012; Hester 2014), and this in a context of changing expectations of the main stakeholders (students, teachers, institutional leaders, entrepreneurs, policy-makers, etc.). These technological and educational changes will undoubtedly have

[1] Current work is focusing on practical implications in terms of pedagogy and didactics, blended learning type approaches (Maritz et al. 2010; Lefevre et al. 2015; Fox et al. 2018; Jones and Lau 2010), and collaborative online learning platforms such as MOOCs (Al-Atabi and Deboer 2014; Cirulli et al. 2016).

important consequences in terms of individual, collective and organizational learning, which are becoming increasingly interrelated (Castaneda and Fernandez 2007; De Freitas et al. 2010; Ceschi et al. 2014).

In the face of these new challenges, the objective of this article is to identify and discuss the opportunities and challenges related to the development and use of Big Data and Artificial Intelligence in the field of entrepreneurship education.

The rest of this article is organized as follows. In a first section, we give a summary of work linking digital technologies and entrepreneurship education. Then, in a second section, we analyze the consequences of the use of Big Data and Artificial Intelligence in the field of higher education. We clarify what we mean by the terms Big Data and Artificial Intelligence, while placing these digital technologies in the context of human history. We then discuss the problem of their use in higher education, regardless of the disciplines concerned. Our third section presents a discussion of the opportunities and challenges generated by Big Data and Artificial Intelligence in the field of entrepreneurship education. To do this, we use an analytical framework that borrows from the theory of teaching models (Fayolle and Gailly 2008) and that has already been used in research to discuss the future of entrepreneurial education research (Fayolle 2013; Nabi et al. 2017). Finally, we propose a research agenda to guide future work in relation to the many questions raised by the implementation of these new technologies in the field of entrepreneurship education.

1. Digital technologies and entrepreneurship education: An overview

Entrepreneurship education, as a practice and research subject, has adapted to technological change much later than in other fields of teaching and research. Indeed, to our knowledge, no studies were published before 2006 on the teaching of entrepreneurship online or via blended learning, and only three studies appear between 2006 and 2009 (Arbaugh et al. 2010). One explanation for this would be the very nature of entrepreneurship, which leads teachers to opt mainly for experiential learning, focusing, for example, on the theory of action (Frese and Sabini 1985; Gielnik et al. 2015), based on the idea that a new activity produces new experiences and ways of thinking (Heinonen and Poikkijoki 2006). Entrepreneurship education thus requires active methods that place the "agent" student at the centre of the learning process (Romero and Usart 2013). Nevertheless, entrepreneurial knowledge is a critical success factor (Welsh and Dragusin 2013) and can be easily digitized, and thus updated, cross-referenced and completed. Three types of initiatives that use digital technologies to link knowledge to action in EE are explored here. To our knowledge, they do not use AI algorithms or Big Data.

MOOCs are both a strategy and a tool to overcome barriers of time, space and financial resources (Cirulli et al. 2016), in order to support the development of students' entrepreneurial potential (Welsh and Dragusin 2013; Cirulli et al. 2016), particularly in developing economies (Welsh and Dragusin 2013). The example of the MOOC devoted to entrepreneurship studied by Al-Atabi and Deboer (2014) shows that the scheme has enabled students to develop their skills, to build international networks beyond barriers of time and space, and to strengthen their entrepreneurial skills and their entrepreneurial intentions.

Blended learning is an educational approach that combines two modes of learning - face-to-face and distance - synchronously or asynchronously (Lebrun 2011), often supported by a learning platform. This approach appears well-suited to entrepreneurship education (Heinonen and Poikkijoki 2006) as it encourages students to broaden their perspectives whilst developing their entrepreneurial skills and behaviours (Maritz et al. 2010). Neck and Greene (2011) suggest entrepreneurship as a method, supported by a portfolio including business creation (coursework), reflective practice, and learning through design, simulations and 'serious games'.

The use of serious games raises questions about their quality, their effectiveness depending on the field of application (Manero et al. 2015) and what they actually evaluate (Calderon and Ruiz 2015). However, they do have a positive impact on learning (Martin et al., 2015), and appear particularly useful for the acquisition of certain gestures (Giannotti et al, 2013) or for the recognition of entrepreneurial opportunities (Fox et al. 2018).

The question then arises of entrepreneurship education as a learning field (Senge 1990), capable of seizing more of the opportunities offered by the digital revolution. Big Data and Artificial Intelligence offer answers to the challenges in this field.

2. The emergence (and consequences) of Big Data and AI in higher education

First, it is important to understand Big Data and AI in order to grasp what they are (2.1.). Then, we will be able to better understand how entrepreneurship teaching and education are being transformed (2.2.).

2.1. Big Data and AI: what are we talking about?

One definition of Big Data is given by George et al. (2014: 321): "*Big data is generated from an increasing plurality of sources, including Internet clicks, mobile transactions, user-generated content, and social media as well as purposefully generated content through sensor networks or business transactions such as sales queries and purchase transactions. In addition, genomics, health care, engineering, operations management, the industrial Internet, and finance all add to big data pervasiveness. These data require the use of powerful computational techniques to unveil trends and patterns within and between these extremely large socioeconomic datasets*."

At the heart of Big Data and AI: In 2001, Laney developed the "Three Vs" model (Laney 2001) to characterize Big Data: Volume (the overabundance of information), Velocity (speed of data production and analysis) and Variety (in reference to the great heterogeneity and complexity of data). This model was adopted in the professional world (by IBM in particular) and in academia by many authors, including Japkowicz and Stefanowski (2016). In 2012, the definition work continued around Laney's initial model. This activity, carried out by the company Gartner, identifies 12 dimensions of data management that interact with one another. Beyer dubbed the whole concept "Extreme Information Management" (Beyer and Laney 2012). These dimensions thus constitute a structural base enabling companies and researchers to develop their studies on data management in a manner adapted to the specificities of organizations. For example, L'heureux et al (2017), who take particular interest in 'machine learning' which analyses data, favour 4 'Vs': volume, velocity, variety and veracity.

According to Boyd and Crawford (2012), Big Data is based on the interaction between technology (which relies on the computing power of computers), analysis (which allows models to emerge from large amounts of data) and mythology (based on the belief that producing and analysing a large amount of data generates much better results in terms of accuracy, truth and objectivity). George et al. (2014) identify five different types of data: (1) public data (2) private data (3) data exhaust (4) community data, and (5) self-quantification data.

In general, Big Data thus offers the opportunity to access an unprecedented abundance of information (Mahmoodi and al. 2017) and to explore the hidden structures of each stratum of the population in order to identify their characteristics (George et al. 2014) in terms of emotions, cognition, motivation, decisions, preferences and interactions of community members (Mahmoodi et al. 2017). On the other hand, their analysis then allows us to observe what brings those people together and distinguishes them from other categories of people (Fan, Han, and Liu 2014). Some researchers, such as Kosinski, Wang and Lakkaraju (Kosinski et al. 2016), propose new methods to identify models and reduce information overload. Big Data also improves the predictive capabilities of organizations (George et al. 2014). In the economic field, unprecedented opportunities thus appear to enable companies to improve their customer relations, innovation processes, and increase their level of competitiveness (Chen and al. 2017; Hartmann et al. 2016).

Algorithms, which are calculation methods (Alexandre 2017), thus produce data. This data is then used by Artificial Intelligences, such as machine learning, which mobilise computer and mathematical systems to reveal information on current and future human behaviour (Krumholz 2014; Zhou et al. 2017). To better understand what AI is and what it is not, we refer to the approach of Poole et al. (1998:1):

> *"Computational intelligence is the study of the design of intelligent agents. An agent is something that acts in an environment—it does something. Agents include worms, dogs, thermostats, airplanes, humans, organizations, and society. An intelligent agent is a system that acts intelligently: What it does is appropriate for its circumstances and its goal, it is flexible to changing environments and changing goals, it learns from experience, and it makes appropriate choices given perceptual limitations and finite computation. The central scientific goal of computational intelligence is to understand the principles that make intelligent behavior possible, in natural or artificial systems.*

> *The main hypothesis is that reasoning is computation. The central engineering goal is to specify methods for the design of useful, intelligent artifacts. Artificial intelligence (AI) is the established name for the field we have defined as computational intelligence (CI), but the term "artificial intelligence" is a source of much confusion. Is artificial intelligence real intelligence?"*

In this sense, Big Data and Artificial Intelligence undoubtedly constitute a new economy that is opening up new entrepreneurial opportunities (Baumol 1996).

Between evolution and Copernican revolution : Big Data is not, strictly speaking, a revolution in terms of data production and management. Sumerian writing (3100 B.C.) already represented a way of externalizing information in human brains and expressing it (Watters 2017; Harari 2016). In this way, information engraved on stones became shareable. The invention of printing, which began in 1450, accelerated the process of externalizing, producing and disseminating information. Fifty years after Gutenberg's invention, about 50 million books had been produced throughout Europe. In other words, for a very long time, man has been confronted with the problem of an overabundance of information that cannot be absorbed by an individual alone (Serres 2014). However, unlike previous developments, the arrival of these new digital technologies is transforming our entire society at a speed never known in human history (Alexandre, 2017).

In this context, the rise of Big Data and Artificial Intelligence in human life is leading us to rethink our relationship to work, to our fellow creatures, to power, to the living and the non-living, and to knowledge, i.e., our way of learning and developing knowledge. Some will say that we are entering a new stage of human civilization (Harari 2016; Alexandre 2017), a stage in which humans are no longer challenged to survive in the living world (we reign supreme) but in which we must now face the threat of what we have invented - Artificial Intelligence and a new virtual continent, Terra Data.

The current development of these technologies in society is under way at a frantic pace, made possible by the exponential increase in the processing power of computers and in the sources and modes of data collection and storage. This is leading to inevitable changes in teaching and research institutions, which will have to work harder to develop the ability to handle knowledge, or in other words, intelligence (Alexandre, 2017).

2.2. How Big Data and AI are transforming education, and hence entrepreneurship education

In the world of higher education, Big Data and Artificial Intelligence are accelerating the transformation of an educational model traditionally tasked with "civilizing each generation of children as if they were a barbaric invasion" (Arendt 1971). The traditional educational model is generally a closed model, limited in its space, specialized in transmitting knowledge in an authoritarian manner by one type of intelligence (that of the teacher), considered superior to other types of intelligence (that of the learner) (Rancière 1991). Today this model is disappearing in favour of an open, permeable system that moves beyond the physical limits of the learning space, crossing disciplines, and multiplying interactions with actors in the environment outside the school, as well as technological tools and ways of learning (McAndrew et al.2010).

Towards a new educational paradigm: The questions raised by the arrival of Big Data and Artificial Intelligence thus invite us to rethink the place of the teacher and the role played by the educational ecosystem within a learning system that is becoming increasingly personalised: “How should the relationship between those providing education and those seeking to learn be approached?” (McAndrew et al. 2010:1). This personalised learning system is strongly linked to the development of an organic system, which encourages interaction and the use of a diversity of data sources and technological tools adapted to the learner's specific needs (Shulman 2016).

In other words, Big Data and Artificial Intelligence are encouraging us more than ever to consider education as a social construct (Lave and Wenger 1991) in which the environment plays a major role in the individual's learning process (Toutain et al. 2017). Technology is considered a resource. It implies the creation of adapted learning environments, facilitating active, engaging and collaborative use of technology (Tritz 2015). Aided by new digital technologies, learning appears to have become an identity creation process (Wenger 1998), allowing learners to define what and how they wish to learn (Seely et al. 2008) by interacting with members of the learning community (other students, teachers, etc.) (Joksimović et al. 2015).

Big Data and Artificial Intelligence are thus based on the further development of knowledge. However, current education (and student demand) is even more focused on learning existing knowledge and the transmission of collective memory to an individual memory. But, if it does not change its traditional form, the school, in the generic sense, is destined to die (Alexandre 2017). In other words, Big Data and AI are totally transforming the definition of knowledge and communities - especially educational institutions - that accompany it. This transformation also involves significant epistemological and ethical changes (Boyd and Crawford 2012). Big Data questions the way knowledge is built, research processes, and more generally, the reading of reality. Should we, for example, as Anderson (2008) suggests, let the figures speak for themselves by abandoning the analysis of human behaviour produced by the human sciences? Who writes the algorithms? How do algorithms evaluate what comes from knowledge? (Watters 2017).

Technologies related to Big Data and Artificial Intelligence are available in the form of a wide variety of tools that support blending learning-based pedagogical approaches (Jones and Man Sze Lau 2010). Stevenson and Zweier (2011) mention the 'flow of learning' concept, which is based on mixing faculty learning (small groups) with help from a teaching assistant and/or a tutor. Mentoring and/or intelligent tutoring via a chatbot (AI that dialogues with a human user) allows the student to progress towards his or her learning goals (Redfield and Larose 2010; Cavanaugh 2017).

Mentored training is personalised and can be done by distance and at university (McAndrew et al. 2010). Students build the learning experience by themselves and move along a pathway previously established with the help of their personal data (interests, previous academic background, professional background, etc.). They learn a lot from home without necessarily going to university. The programme is varied and includes digital textbooks, participating in MOOCs (Al-Atabi and DeBoer 2014; Passarelli 2014; Waard et al. 2011; Cirulli et al. 2016) and E-Conferences (Shi and Morrow, 2006), and carrying out assignments based on structured[1] and non- structured[2] data (Bryant 2017). The student also participates in certain activities, for example, courses based on experimentation in the form of small group practical projects guided by a teacher, participation in a video game (Martín-San José et al. 2015), or immersion with total interaction via virtual reality: "immersive learning will surpass active learning, which in its day surpassed passive learning in effectiveness" (Cavanaugh 2017: 9).

At the university level, the analysis of data produced through Big Data and Artificial Intelligence can strengthen the quality of teaching programmes, student monitoring and strategic decisions in order to adapt more quickly to educational needs (Daniel 2015). In this way, the future development of 'machine learning', which does not require explicit programming, will facilitate the analysis of data and thus help educational institutions to function more efficiently. These machines have the ability to extract and analyze useful information from the mass of data in order to offer concrete solutions to academic problems. For example, "how do you identify a group of students who need an additional scholarship to keep them in university?" (Yates and Chamberlain 2017). On another level, machine learning methods improve knowledge of what students learn from their learning experiences and the type of experience that occurs (Grimmer 2015).

In short, the integration of technological tools is profoundly transforming ways of learning by placing the student at the centre of the learning process, and ways of creating learning situations (teaching) by placing the teacher in the situation of orchestrator of activities.

Artificial Intelligence and Big Data also offer new solutions for creating and managing academic programmes, how universities function, and for monitoring students as they move along their personalised study pathway. According to some authors, these major transformations require bringing the world of education closer to that of computer science (Tritz 2015). In addition, it is a question of creating new forms of leadership based on the unification of academic technologies with the development of Big Data and Artificial Intelligence in order to support students (Shulman 2016).

Implementation issues:_The current development of new digital technologies in higher education raises questions similar to those asked when books dispossessed scholars of their role

[1] Answers to closed questionnaires, evaluations by statistics such as response rates, completion rates, course attendance rates, ...

[2] Discussions, learning content created by the student in interaction with colleagues via platforms managed by Artificial Intelligence.

as producers and disseminators of knowledge: what to do with this immense external storage capacity for the information produced? Which pieces of information are necessary to allow students to deepen their knowledge of a subject, to the point of eventually becoming an expert? How durable is the knowledge acquired? (Serres 2014; Watters 2017).

Like books, Artificial Intelligence and Big Data can contribute to improved learning by providing a rich and easily accessible digital environment for learning different subjects, such as mathematics (Brown 2015). What's more, the use of these technologies in higher education frees time and frees up the brain from dealing with certain technical and rational knowledge, making it possible to focus attention on the development of imagination, creativity, inventiveness, reflexivity and emotional awareness (Pink 2006; Serres 2014). Other researchers stress that the arrival of Big Data and Artificial Intelligence in all sectors of society will force educational institutions to radically transform themselves (something they have not been able to do for several centuries), by focusing more on experimentation and the development of an intelligence which is no longer based on memorization. Rather than learning in silo, education will be about multidisciplinarity, as well as the ability to mobilize resources, develop meaning, and apply critical thinking, whilst leaving plenty of space for experimentation (Alexandre 2017). This approach to education today represents a real challenge for teachers, who must review their teaching practices, as well as for students, who are not used to learning primarily from the development of these types of cognitive abilities (Cavanaugh et al. 2016).

Future knowledge development relies on the mobilization of three forms of memory: human memory (partial, contingent, malleable, contextual, erasable, fragile), material memory (permanent, stable, unchangeable) and digital memory (easy to erase, stored in files that may become obsolete, reliant on electricity and batteries that are rare elements dependent on the environment and politics) (Watters 2017). The combination of these three memories is a source of complexity and fragility. Watters (2017: 44) points out that "humans created more information when they moved from stone to paper and from handwriting to machine printing. But what they have gained in efficiency, they have lost in durability".

In other words, if quantitative data production takes precedence over qualitative production, our collective memory may be at risk in this abundance of digital information (Boyd and Crawford 2012; Droll et al. 2017). With this growing body of data, researchers will thus have to be able to avoid misinterpretations: the models discovered may be false (Prinsloo et al. 2015). They will also play a very important role in rigorously cross-referencing public and private data to produce quality statistics on economic behaviour (Einav and Levin 2014). But not all researchers operate in the same way. Grimmer (2015) points out that social scientists use machine learning algorithms to measure quantitative characteristics or effects, while computer scientists use data more as a predictive tool. However, whether they are social scientists or computer scientists, they will have to face the blurred boundary between public and private information (Kosinski et al. 2016).

As already mentioned, the qualitative use of Big Data should make it possible to better personalise study pathways by improving, for example, students' knowledge of their own personalities, which means not just a fixed description of their characteristics but also understanding their cognitive processes, i.e., their ways of acting, thinking and expressing themselves (Boyd and Pennebaker 2017). These digital technologies, including social platforms and networks, play and will continue to play a crucial role in strengthening collaborative and social learning by improving information selection, enabling learners to connect with the right people and motivating community members who contribute and collaborate (Al-Dhanhani et al. 2015). That said, we might ask whether Big Data and Artificial Intelligence, which make part of the future predictable, run the risk of hindering the creative potential of learners if not accompanied by an adapted pedagogy that engages the freed-up part of the human brain? (Sarasvathy 2003). Either way, these technologies represent a significant investment, which will require schools and universities to closely study their effectiveness (Maritz, Brown, and Shieh, 2010). The mobilization of these new learning resources therefore questions the nature of the knowledge produced and the evaluation of learning, as has been seen in the case of video game use (Calderón and Ruiz 2015; Manero et al. 2015; Fox and al. 2018).

More generally, the evolution of knowledge production via Big Data and Artificial Intelligence will initially raise questions of governance: who will write future algorithms? How will algorithms assess what emerges from knowledge and memory? Which knowledge, which histories, which memories should be preserved? Who will control the memory machines?... (Watters 2017). Secondly, the new knowledge produced raises the question of ownership: when a student produces new knowledge on platforms, with the help of a digital mentor, who will own it? The company that owns the platform? The college? The student?... Thirdly, in the future, how will it be determined which knowledge comes from collective memory? Finally, how long will this collective memory last? (our ability to develop and maintain it depends on the storage strategies of the few companies that own the platforms). How long can we keep it when today the average life of a URL is 44 days? (Watters 2017).

3. Opportunities and challenges for entrepreneurship education: For or against data-driven entrepreneurship education?

Digital technologies, and more particularly Big Data and Artificial Intelligence, are profoundly transforming the teaching of entrepreneurship. Based on the work we have identified and using the theoretical framework of teaching models (Béchard and Grégoire 2005, 2007; Fayolle and Gailly 2008), we propose in this section to review the main opportunities (3.1.) and challenges generated by these new technologies (3.2.).

The Teaching Model approach distinguishes between two levels (ontological/paradigmatic and didactic) and questions, at the didactic level, the main dimensions which characterise on an operational level any teaching or learning process (objectives, audiences, pedagogies, contents, indicators and evaluation methods).

3.1. Ontological Opportunities (what does education mean in the context of entrepreneurship? What are the specific roles played by educators and participants?)

Big Data and AI will change our understanding of entrepreneurship education and the roles and positions of learners and teachers in entrepreneurship learning situations.

The educational aim of an entrepreneurship education system is to train the development of entrepreneurial intelligence based on the ability to select information, analyse it critically and creatively in order to give it meaning and transform it into actionable knowledge. The teaching of entrepreneurship 4.0 involves changes in the student and teacher through the use of digital technologies. Big Data is changing the definition of knowledge, with a need to articulate old and new forms of knowledge (Boyd and Crawford 2012). The student becomes an entrepreneur, author and cooperator, constantly adapting to rapid and unpredictable changes in the environment. The teacher becomes a coach, a creator of learning situations integrating digital tools, resources and production, in connection with the business environment and its stakeholders.

However, Big Data is creating new digital divides (rich/poor) on data access issues as well as on skills, notably computational skills (how can we teach students data analysis skills if they are not data scientists themselves?). In other words, the availability of Big Data limits the types of questions that can be asked and reinforces inequalities (Eynon 2013), especially if access to the Internet as well as to digital technologies and tools is non-existent or inefficient in certain contexts and educational environments.

3.2. Didactic opportunities

The educational opportunities relate to new content, new learning methods, but also interactions between teachers and learners and the development of interactive communities.

New content and learning methods: In the future, training involving AI and Big Data, and the nature of the knowledge to be acquired, will be modified, as will the learning experience itself. A number of skills must be developed, requiring training and individual and collective appropriation. The challenges are to train students in i) cooperation through the use of pedagogical approaches that combine individual working hours, experiential learning, and the mobilization of AI and Big Data for the development of their projects; ii) the use of a large quantity of data sources and technological tools (Shulman 2016); iii) data analysis, notably through the development of metacognitive intelligence and critical thinking.

Supporting student entrepreneurs' learning through digital technologies means taking into account several components of the learning process. Educators need a better understanding of students' needs; for example, teachers of business models can draw on research showing that types of business models are linked to data as a resource (Hartmann et al. 2016). Digital tools like smartphone sensing can help to better understand the personalities (Boyd and Crawford

2012) of student entrepreneurs, by studying the traces they leave in the digital world, at the same time as or after their actions (analysis of exchanges on social networks, teaching platforms). While the rules of the game are now changing very quickly within the entrepreneurial ecosystem, data collection and processing to search for information (Kravvvaris and Kermanidis 2017) provides entrepreneurial students with valid knowledge to guide their action choices, such as detecting business opportunities through machine learning (Zhou et al. 2017). This data, collected and analysed, could give access to better knowledge of the actions of student entrepreneurs and their perceived effects by stakeholders. Their entrepreneurial behaviour in the real world can also be analysed, as is that of entrepreneurs (Uy et al. 2010), via the use of smartphone sensing (Gosling 2014), which addresses the limitations posed by questionnaire approaches (Harari 2017). Finally, creating learning situations to develop students' skills in data analysis and computational skills gives them the opportunity to create new business creation processes (von Briel et al. 2018).

The contributions of machine learning to entrepreneurship learning remain to be explored. For example, could it play a role in developing stakeholder networks, learning risk-taking or entrepreneurial decision-making?

New learner-teacher interactions: A large amount of data and information is accessible thanks to digital technologies. Educational support with using research and information processing tools in entrepreneurship education is necessary to enable students to sort data and transform collected information into entrepreneurial knowledge. For example, the student learns to distinguish information or knowledge that can quickly become obsolete from key knowledge, which is useful for learning (Watters 2017). The teacher helps students to identify the information that constitutes knowledge required to allow them to deepen their knowledge of a subject until they reach an expert level. Teachers create the conditions that allow students to access data as freely and easily as possible (for example, information about markets, or testimonials from entrepreneurs relating to students' needs (Stevenson and Zweier 2011), to cooperate with their peers in a synchronous, asynchronous, face-to-face or remote manner, and to decide freely, within a predefined pedagogical framework, on the rate of progress of their learning and the tools they will use. Favouring "adaptive learning" (Alexandre 2017), the teacher creates a new pedagogical relationship to support the student in enabling autonomous learning; the training thus adapts to the ultra-personalization of each student's entrepreneurial pathway. The use of student-centred pedagogy implies less face-to-face time and more time involved in individual or team learning, and the teacher employs new ways of teaching using the extra learning time obtained through the mobilisation of AI tools (MOOCs, Chatbots, individualised work plans via platforms, and so on) (Alexandre 2017).

Emergence of educational communities: This transformation of entrepreneurship education teaching methods requires training teachers and the education community (including external stakeholders, such as entrepreneurship professionals and entrepreneurs/business leaders) in the acquisition of new pedagogical methods focused on the student's individualized pathway. EE 4.0 is inherently complex because it implements multidisciplinary skills, and its educational community must respond to a number of challenges. It must explore and experiment with ways of creating multidisciplinary teaching teams to train for entrepreneurship that draws on hybrid knowledge (technological, human, economic)(Tritz 2015); create plural learning environments (from home to school), adapted to facilitate the use of technologies in an active, engaging, collaborative way (Tritz 2015); and mobilize, with the help of AI and digital tools, the data produced by the student in order to evaluate the progress and results of students' entrepreneurship learning. Do these changes require a redefinition of the teacher's role vis-à-vis "intelligent tutors/mentors"? (Redfield and Larose 2010).

3.3. Challenges, limitations and risks

Several limitations and risks relating to the use of Big Data and AI in EE can be identified. First of all, the ethical dimension of the collection, storage, processing and use of this data raises questions. Indeed, the question of data transparency is central (Nosek et al. 2015), as is its source - public (open data) or private (Kosinski et al. 2016).

Whilst smartphone sensing is a promising tool for acquiring knowledge about the personalities and behaviours of entrepreneurial students, questions arise about the security of the data collected, its storage, and the professional use made of a personal smartphone (Parham et al. 2015).

In entrepreneurial society (Obshonka 2017), the quasi-monopoly of GAFAM in data collection and the political commitments of some of their chief entrepreneurs is likely to upset the balance of regulatory forces (market, laws, social standards, code-architecture) (Boyd and Crawford 2012) and is already impacting the higher education market and more specifically, entrepreneurship education. University-industry partnerships are currently emerging in American (MIT or Northwestern) and European (emlyon business school) universities, notably involving IBM and Apple.

Next, on a methodological level, Big Data approaches must be combined with more traditional approaches (Mahmoodi et al. 2017) to reflect the richness of the environment, and the detail of human thoughts and actions. It is not possible, for example, to measure constructs such as recognition or opportunity creation using Big Data and related tools (Audretch 2012).

Finally, machine learning makes it possible to identify patterns not previously envisaged, but which in no way replace human creativity and can be a source of errors (correlations which actually only have mathematical meaning). According to Sarasvathy (2003), Big Data could diminish Simon's limited rationality and creativity. What use is Big Data for designing and building the world, not just studying it? For Venkataraman et al. (2012), opportunities are artifacts. Their very existence transforms the world they inhabit in by creating new opportunities. AI and Big Data are thus objects that are now part of our world. They interact with its components by drawing new relationships and thereby transforming the environment.

4. Research agenda

The ongoing technological changes, opportunities and challenges that we have identified suggest multiple avenues of research in terms of teaching models at different levels and dimensions, as well as in relation to teaching and research institutions, which are experiencing technological disruption.

4.1. Level of educational and research institutions in entrepreneurship education

Educational and research institutions will be confronted with the need to invest massively in data centres, to recruit data scientists and to establish partnerships with specialised operators - private companies in the field of education. What's more, the changes under way will have consequences for the management of professorial resources, particularly in terms of recruitment and training of teacher-researchers. Under these conditions, research focusing on adaptation strategies and changes in the organizational behaviour of teaching and research institutions could help identify key factors and good practice in this area. Furthermore, studying the impact of the entrepreneurial culture (and/or orientation) of institutions on their ability to engage in and succeed at technological change would be an interesting perspective at a time when the benefits of the entrepreneurial university are being highlighted (Fayolle and Redford 2014).

Another useful direction for future research would involve gaining a better understanding of the most appropriate structures for the evolution of entrepreneurship-related educational systems and methods. Should existing structures (department, research centre, business centre, etc.) be used or is it necessary to set up new structures?

With respect to faculty resources, should teacher-researchers in entrepreneurship education be trained in data analysis and interdisciplinary teamwork (like data scientists/social scientists) or should other types of educators and researchers be sought out and recruited?

4.2. Ontological/paradigmatic level

An important consequence of Big Data and AI concerns the evolution of teaching models specific to the field of entrepreneurship. Béchard and Grégoire (2005, 2007) have identified five theoretical models, which have been taken up in recent research (Nabi et al. 2017). Do the transformations induced by the use of digital technologies contribute to the emergence of new theoretical models or can they be integrated into existing models?

For example, as in the case of medical education (Krumholz 2014), entrepreneurship education could offer personalized and predictive teaching based on new methods of classifying teaching models, profiles of student entrepreneurs, with, for example, subcategories linked to patterns that are recognizable according to factors identified through machine learning. A new way of conducting research in entrepreneurship education could also emerge. Machine learning makes it possible to identify patterns and/or correlations between data submitted for processing, without a research question having previously been submitted. AI could investigate data relationships even though EA researchers have not yet identified these relationships or any potential interest in relation to their field of research.

The implementation of Big Data and AI also questions teachers' ethics, values and beliefs, particularly in relation to technology. To what extent and under what conditions, for example, can the hybridization of individual, collective, relational, emotional and artificial intelligences be achieved in order to have balanced and sufficiently distant educational systems? To what extent can the technological beliefs of entrepreneurship educators influence the design and implementation of educational systems? What influence can a passion for digital technologies have on the design of roles that teachers take on? What interactions might there be between the different things that people are passionate about: for education, for entrepreneurship, for digital technologies?

Finally, with regards to the roles of teachers and students, questions arise about the evolution of positions over time. While many teachers see themselves more as transmitters of knowledge, how can they be persuaded to adopt the role of facilitator and orchestrator?

4.3. Didactic/pedagogical level

Big Data and AI will profoundly transform content, pedagogies, teacher-student relationships, and evaluation processes and indicators. In this context, it is essential that research in the field of entrepreneurship education accompanies and documents these changes.

Research might focus on entrepreneurial knowledge and skills that are useful and necessary in a digital world. In addition to skills enabling the recognition and exploitation of opportunities, the generalisation of digital technologies in the economy and their use in educational systems raises questions about the need to develop social knowledge and skills, facilitating interaction, cooperation, collective work and group learning. From this point of view, work on networks and entrepreneurial teams (including student teams) would benefit from being intensified and technologically contextualized. Clearly, it is not enough to focus on the nature of knowledge and skills. Another question concerns the educational mechanisms and processes for developing them. Research projects could focus on the design of such initiatives, the opportunity to combine methods and tools, and the type and level of interaction between teachers and students.

An important dimension of didactics is to have a good understanding of students' needs/expectations and a thorough knowledge of their psychological profiles and characteristics. At this level, Big Data and AI can provide teachers with very satisfactory solutions to this dual objective, particularly from a dynamic and longitudinal perspective. There are also research questions to be studied on this issue. If, technically, it seems possible to 'follow' students along their educational pathways and to personalise entrepreneurship teaching, how can such systems be designed and integrated into teaching in practice? How to ensure their relevance and robustness? How can security of personal data and confidentiality be ensured?

Big Data and AI are likely to revolutionize entrepreneurial pedagogy, particularly through the use of machine learning and chatbots. To our knowledge, no practice using these technologies in the field of entrepreneurial education has been documented to date. There is progress to be made and the possibilities are considerable. To what extent, for example, can chatbots replace teachers, and for what type of interventions? What could be the role of machine learning in the learning processes of business creation teams? To what extent can this technology contribute to facilitating access to the most influential/determinant networks at a given time? Can it help with risk-taking and entrepreneurial decision-making by proposing the best possible scenarios at the individual and collective levels? How can these advanced technologies be integrated into teaching and with what expertise? What role is there for multidisciplinary teaching teams bringing together entrepreneurship teachers, education researchers and data scientists?

Ultimately, research that can be rapidly transferred into pedagogical practice could aim to identify patterns of entrepreneurship education initiatives that are effective in terms of achieving initial objectives via the use of machine learning, natural language analysis and, more broadly, digital traces left on the Web.

Generally speaking, digital technologies, especially the most advanced, are changing the levels of knowledge and expertise of teachers and teaching staff. The variety of knowledge and skills required demands an evolution towards multidisciplinary teams. In previous work (Fayolle 2013; Fayolle et al. 2016) we have already demonstrated, both in terms of practice and research, the need to connect the fields of entrepreneurship and education. We believe that it is henceforth essential to add other disciplines (notably computer sciences, and cognitive sciences). The teaching of entrepreneurship should therefore move from a very individual practice towards encompassing, at least in the design and experimentation phase, multidisciplinary points of view and expertise. Research can therefore focus on disciplines, balance between disciplines, cohesive factors, and the respective roles of multidisciplinary teaching teams whose objective is to develop entrepreneurship education based on the use of the most advanced digital technologies.

Research into the evaluation of entrepreneurship education has increased in recent years, but we are still far from having a good knowledge of the impact of such training programmes (Nabi et al. 2017). The digitalisation of teaching will increase the need to know more about this aspect. There are many lines of inquiry worth pursuing. These might include: What is the impact of MOOCs, blended learning, and Serious Games on student learning and behaviour? What are the effects of Big Data, AI and their pedagogical consequences (traceability, personalisation of pathways, easier access to data and good practice, synchronisation of students' needs and responses, etc.) on the short and long-term effectiveness of entrepreneurship education in terms of developing attitudes and entrepreneurial intentions and going through with setting up a business? What are the effects of digital technologies on the quality of teamwork, the development of entrepreneurial projects, and on the quality and intensity of collective and individual learning within groups?

Conclusion

In conclusion, we believe that the use of digital technologies in the field of entrepreneurial education will allow major advances in research to be made.

Indeed, one of the major difficulties today in terms of research design is to be able to study processes and dynamics of behaviour and learning using longitudinal methods with real time data. Big data and AI, in particular, will make it possible to design research projects involving three types of actors engaged in win-win relationships: students (or learners), teachers/facilitators/orchestrators, and researchers. Students will benefit from the initiative because it will enable them to personalize their career paths, taking precise account of their profiles, needs and expectations, and providing the answers to the kinds of questions they ask themselves, and so on. For teachers, benefits will include, among other things, closer connections with researchers, enabling them to benefit from the knowledge and insight with regard to particular situations. For researchers, the initiative will allow them to study individual and/or collective learning processes, interactions between students and teachers, and the influence of a multitude of endogenous and exogenous factors in a longitudinal way and from data obtained in real time, i.e., as events occur.

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