



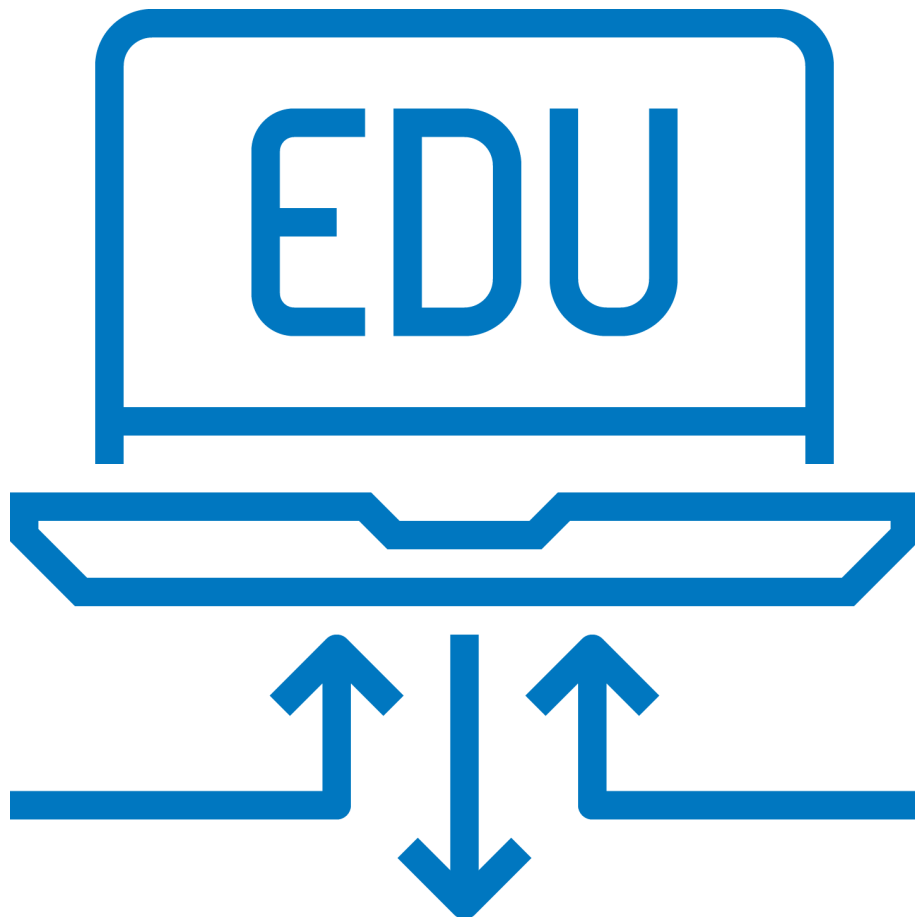
LRE Sub-Committee

White Paper #1

A review of the state-of-art of the use of
machine-learning and artificial
intelligence by educational portals and
OER repositories

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LRE SUBCOMMITTEE BACKGROUND AND REMIT

Since 2002 European Schoolnet has engaged in a series of projects involving its supporting Ministries of Education (MoE) aimed at building access to open digital learning resources. To make digital learning content interoperable and easily discoverable, EUN and its partners have particularly developed, tested, and deployed 'brokerage system' architectures and services in the course of successive EC sponsored projects (CELEBRATE, CALIBRATE, MELT, ASPECT and eQNet).

Along with unlocking the free digital content previously difficult to find in dispersed repositories, EUN and its partners have engaged in research on best practices and services related to: the distribution and creation of user generated open content; the application of digital content packaging standards and specifications; the development of pedagogically relevant metadata standards and profiles; and the adoption of strategies to enhance the linguistic and cultural components of Open Educational Resources and Open Educational Practices.

Over the last ten years in a series of small and large-scale school validation pilot projects in Europe, EUN and partner MoEs have built, tested and managed platforms and portals dedicated to fostering communities of practice in sharing expertise, producing user generated resources and distributing open educational content produced by MoEs and other content providers (under a variety of open licenses, including Creative Commons).

One of the best known and self-sustaining long term outcomes of this work is European Schoolnet's Learning Resource Exchange for schools (<http://lreforschools.eun.org>), an infrastructure comprising a catalog of Open Educational Resources (currently there are more than 330,000 resources referenced in the catalog) representing almost 100 content providers.

Today European Schoolnet's mission to support the uptake and exchange of Open Educational Resources in the European K-12 sector is being taken forward by a group of European Ministries of Education and other organisations that are part of its Learning Resource Exchange Subcommittee (<http://lre.eun.org>).

The LRE Subcommittee is open to regional and local education authorities and private for-profit and non-profit organizations that wish to utilise LRE services and take advantage of available benefits. Members participate in European and international projects investigating the impact and best practices of OERs. To foster networking opportunities, the LRE Subcommittee also collaborates closely with EdReNe, a network of European repository nodes and stakeholders dedicated to the development of recommendations and exchange of expertise.

LRE SUBCOMMITTEE MEMBERS

MISSION: TO SUPPORT THE UPTAKE AND EXCHANGE OF OPEN EDUCATIONAL RESOURCES IN THE EUROPEAN K-12 SECTOR



<http://lre.eun.org>

A REVIEW OF THE STATE-OF-ART OF THE USE OF MACHINE-LEARNING AND ARTIFICIAL INTELLIGENCE BY EDUCATIONAL PORTALS AND OER REPOSITORIES (WHITE PAPER)

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ABSTRACT

In this report, we provide an overview of the most prominent Artificial Intelligence (AI) and Machine Learning (ML) practices used in educational contexts focusing on Open Educational Resources (OER) and educational portals aiming to support K-12 education. To that end, we will provide definitions and descriptions of relevant terms, a short historical overview of Artificial Intelligence (AI) and Machine Learning (ML) in education and an overview of the goals and common practices of the use of computational methods (AI and ML) in educational contexts. We will present the state of the art with respect to the adaptation and use of computational methods in educational portals and OERs and we will discuss the potential benefits and open challenges that may arise from these practices. This report concludes with future directions that could support local structures and directives to move forward with the integration of computational approaches to existing OER and educational portals.

1 Introduction

The rapid adoption of technological advancements, along with the (big) data revolution in education, have provided numerous learning opportunities for stakeholders (that is educators, learners, curriculum developers, program directors, learning content creators and researchers). For example, the adoption of technology in education has provided us with new tools and methods to support learning and teaching. At the same time, users of educational technologies can become part of large learning communities or communities of practice and learn together with peers who are physically located in different places. With the increased popularity of online courses, it soon became evident that there is a need for educational resources and learning content – from textbooks to videos and podcasts – that would be openly available and freely accessible for every stakeholder, that could be re-distributed and re-used in different settings and that could be adapted to meet the needs and interests of different learners. This need for suitable resources and content led to the emerging concept of Open Educational Resources (OER) and educational repositories as a means of scaffolding educational transformation (Butcher, 2015).

The OER movement created manifold opportunities for learners, teachers and educational institutions since they gained access to a plethora of resources and content. Learning materials can nowadays be easily distributed, shared and adapted to meet learners' needs and interests. Data richness offers new opportunities for testing analytical approaches to facilitate and inform new or revisited paradigms. Thus, there is a unique opportunity to employ cutting-edge computational approaches to address fundamental pedagogical challenges such as: how to adaptively guide students and how to provide appropriate scaffolding to facilitate learning and to improve learning outcomes.

At the same time, in order to benefit from aforementioned technological advances in education, we need to address certain challenges that have been raised through those advances. With the amount of learning material increasing, we need to ensure that materials are accessible to the general population. Most importantly, it is necessary to set quality standards for the learning material we distribute, and we have to ensure that these materials meet those quality standards. On the other hand, due to the vast amount of learning content that is offered, learners face the challenge to efficiently and effectively choose learning material to accommodate their requirements. This indicates a need for tools to support learners when choosing appropriate learning content.

However, providing material to learners alone is not enough. In the digital age, we want learners to acquire the kind of competencies and skills – the so-called 21st century skills (Bell, 2010) – that will lead them beyond the acquisition of inert knowledge and that will support them in using new technologies and digital resources in an efficient and effective way in order to achieve their goals. Therefore, besides materials, we have to provide learners with the tools that will support reflection and self-regulation, scaffold collaboration and communication, foster information and digital literacy and promote creativity and critical-thinking. Finally, we should raise awareness regarding challenges that learning in the digital age may bring along, such as data ownership, privacy and security.

1.1 Purpose of this report

In this report we aim to identify and review best practices in the use of Artificial Intelligence (AI) and Machine Learning (ML) technologies in educational research, focusing on the context of educational portals, OER repositories and K-12 education. We will elaborate on the state-of-the art of AI and ML in education and we will also provide a vision on how AI and ML can be promoted and used to better serve teachers and learners. In the next sections we will discuss the expected

benefits from the use of computational methods in education and the potential risks and opportunities such practices may entail. We will attempt to identify the relationships between open and reusable learning content, data ownership, technical challenges and privacy aspects. Finally, we will conclude with a discussion about future directions regarding the use of computational approaches in OER and educational platforms as well as how we could promote and orchestrate common actions from stakeholders in order to support advancements on a European level.

2 Artificial Intelligence and Machine Learning: Definitions and Historical overview

In computer science, we use the term Artificial Intelligence (AI) to describe computational technologies that allow machines (that is, computers) to act and take decisions imitating human behavior and intelligence (McCarthy, 1998). Machine Learning (ML) is a subfield of Artificial Intelligence, in which statistical methods and computational algorithms are being used to teach machines through examples and by experimentation with data on how to perform specific tasks (Michalski, Carbonell, & Mitchell, 2013).

Research regarding the use of AI and ML in education has been ongoing since the late '70s and '80s when the first computer-assisted instruction (CAI) and intelligent tutoring systems (ITSs) were developed (Nwana, 1990). In the early days, AI methods were employed in two ways:

- a) to design and facilitate interactive learning environments that would support learning by doing. In such environments, students received guidance to learn through their experiences while they were experimenting with interactive computer artifacts. An example of this research line is the work of Seymour Papert introducing an educational programming language called LOGO for teaching geometry (Papert, 1980);
- b) to design and implement tutoring systems, that is computational systems that “imitate” human tutors and gradually support students in mastering skills by adapting instruction with respect to the student's knowledge state (Corbett, Koedinger, & Anderson, 1997).

Thus, we could say that AI has originally been used either as a learning tool itself so that students could learn by experimenting with AI algorithms or as a technology to support the personalization of learning environments and the adaptation of instruction to learner's needs and personal goals.

On one hand, Papert's constructionist approach was originally criticized since it demanded radical changes to the educational status quo (Nwana, 1990). However, it strongly influenced modern educational programming languages and programming environments that are nowadays used widely, such as Scratch¹ or educational approaches that explore the use and programming of robots as a means of facilitating and promoting STEM education².

On the other hand, the practice of Intelligent Tutoring Systems (ITSs) was widely adopted in K-12 and Higher Education demonstrating promising results and outcomes. In a meta-analysis of research that aims to compare the effectiveness of human tutors with the effectiveness of ITSs, it became evident that ITSs are almost as effective as human tutors with respect to problem-solving and reading activities (VanLehn, 2011). ITSs' success is largely due to the fact that such systems are capable of tracking student performance and to choose appropriate content for practicing skills and fostering knowledge tailored to the individual student's needs. To achieve that, ITSs use student models that are implemented using AI and ML methods and that are based on the idea of "*mastery learning*": that is, the student is asked to continue solving problems or answering questions about a concept until s/he has mastered it. Only then will the student be guided to move forward to other concepts. We will provide an overview of state-of-the-art student modeling methods used in ITSs alongside best practices in following paragraphs. However, despite the positive outcomes demonstrated by the use of ITSs, their practice has been criticized for not considering the social aspects of the learning process, for the lack social interaction and for not promoting the acquisition of social skills. For ITSs, the student is considered an individual unit who learns while practicing with learning material. Nonetheless, learning is not only about providing knowledge and mastering skills, but also about integrating students in a structured society of information and knowledge (Hawkins, Sheingold, Gearhart, & Berger, 1982).

¹ <https://scratch.mit.edu/>

² <https://robohub.org/work-play-and-stem-how-robotics-will-bridge-the-gap/>

The breakout of e-learning practices in online and massive online open courses (MOOCs) addresses the aforementioned criticism, since they provide the opportunity to learn in a social arena thus allowing students to interact with instructors and their peers. At the same time, we aim to promote personalization of online learning and to provide learners with unique, adaptive and personalized feedback and support. Furthermore, due to the large number of data traces that are produced from learners' online activities, there is a need for cutting-edge, computational approaches for processing and analyzing learner's activity as captured by logfiles and for providing adaptive feedback that addresses learner's needs and considers individual learner characteristics. In this context, AI and ML methods promise to fill in the gap and offer solutions³.

3 AI and ML approaches in education: an overview of the state of the art

There are three main research lines that explore the use of AI and ML methods in the context of computational and online learning systems and environments:

1. **Student modeling and personalized feedback:** Research in this field studies the use of computational methods to assess student's background knowledge, to model student's knowledge state and to predict student's performance. Student models are commonly used in educational platforms and intelligent tutoring systems in order to provide indications about student's knowledge state. These indications are then used to guide their learning activity by providing adaptive, personalized feedback, tailored to the learner's needs and personal characteristics taking as an example the effective practice of the one-to-one tutoring paradigm (Bloom, 1984).
2. **Recommendation systems:** Research in this field focuses on intelligent methods for choosing appropriate study materials, learning activities, examples and exercises with respect to the learner's needs and interests.
3. **Computational tools to support teachers:** Research in this field studies the use of computational tools to support either teachers' training (by providing

³ <https://www.mckinsey.com/featured-insights/artificial-intelligence/the-role-of-education-in-ai-and-vice-versa>

evidence or assessments regarding teachers' competencies and skills as well as recommendations about how to improve their pedagogies) or to support teachers' practice (usually by providing indications from students' activities on the individual or on the classroom level through applications commonly known as teacher dashboards).

Research in these lines usually intertwines and complements. Here, we provide an overview of typical AI and ML methods used in each area in educational research in general and in OER and educational portals in particular. We also discuss some examples of AI and ML technologies integration into the European K-12 sector.

3.1 Student modeling and personalized feedback

Student models are typically used in Intelligent Tutoring Systems and learning platforms in order to model and assess student's performance. Most student models are either cognitive or statistical. Cognitive models represent the structure of the internal reasoning system which students use to solve problems while statistical models use latent factors that explain observed performance data in order to predict student's performance. AI methods, such as Bayesian networks, or machine learning algorithms, such as logistic regression, are used to design and train these models.

One of the most well-established practices in student modeling is the use of cognitive models in cognitive tutors. By cognitive tutors, we refer to the ITSs that were established by Carnegie Learning⁴ and are based on the ACT-R (Adaptive Control of Thought-Rational) theory of human cognition (Anderson, 1996).

Most cognitive student models are based on the notion of mastery learning. Only when a student has mastered a concept, will s/he be guided to move forward to other concepts (Corbett et al., 1997). Mastery learning is in line with the notion of learning curves that is, how many opportunities a student needs in order to master a skill or knowledge component. In order to assess mastery, ITSs use student models that predict the performance of students on various steps of a learning activity. Based on these predictions, the tutoring system chooses what kind of content or scaffolding to provide to students and if further practice is necessary (Chounta, Albacete, Jordan, Katz, & McLaren, 2017).

⁴ <https://www.carnegielearning.com/>

Typically, cognitive student models predict step outcomes – that is whether a student will carry out a step-task correctly or not – based on the skills involved in this step and student’s prior practice. There are two main AI/ML modeling approaches that dominate cognitive modeling:

BAYESIAN KNOWLEDGE TRACING (BKT) MODELS

Bayesian Knowledge Tracing models use data that reflect student’s performance to predict the probability of a student knowing a skill at a given time (d Baker, Corbett, & Aleven, 2008). The response from the model is binary, this means that the model predicts either positively (for example, the student knows the skill and therefore the student will answer correctly) or negatively (for example, the student does not know the skill and therefore the student will not answer correctly). To compute this probability, the model takes into account four modeling parameters on every practice opportunity: a) the probability that a student knows the answer before the activity even begins; b) the Guess parameter that indicates the probability that the student will guess the correct answer; c) the Slip parameter that indicates the probability that the student will slip and give an incorrect answer although s/he knows the correct one; d) the probability of the student learning the skill. Bayesian Knowledge Tracing models are implemented as dynamic Bayesian networks (Yudelson, Koedinger, & Gordon, 2013). In order to fit the modeling parameters, the BKT models are trained using data from student’s prior practice.

LOGISTIC REGRESSION MODELS

Logistic regression models use student-specific and problem-specific parameters in order to predict student performance. For example, the Additive Factors Analysis Model (AFM) - introduced into ITS research by Cen et. al. (Cen, Koedinger, & Junker, 2008) - predicts the likelihood of a student correctly completing a step as a linear function of student parameters (the student’s proficiency), knowledge components or skill parameters (the difficulty of the knowledge components or skill involved in certain questions or tasks) and the learning rates of skills. AFM considers the frequency of prior practice and exposure to skills. In addition to AFM, the Performance Factors Analysis Model (PFM) (Pavlik Jr, Cen, & Koedinger, 2009) considers whether prior practice was successful (that is, how many times a student answered correctly or incorrectly) and the Instructional Factors Analysis Model (IFM) (Chi, Koedinger, Gordon, Jordon, & VanLahn, 2011) also considers the tells (that is, how many times the tutor gave away the answer of the next step directly instead of eliciting).

Apart from ITSs, these student models are used in open online courses, such as the courses implemented as part of the OER Open Learning Initiative by Carnegie Mellon University⁵, in order to assess student’s performance in learning activities and to provide recommendations.

⁵ <http://oli.cmu.edu/>

In other educational settings, like for example in MOOCs, student modeling extends beyond modeling individual student's performance. Since the social aspects of learning are particularly important for MOOCs, it is common to use ML techniques, such as block modeling and social network analysis to model students with respect to their social profile or to model the knowledge flow as a proxy for learning (Hecking, Chounta, & Hoppe, 2017). Similarly, in collaborative learning scenarios that aim to support K-12 learning activities, time-series analysis has been used as a tool for assessing the quality of collaboration between peers (Chounta & Avouris, 2015). These assessments can be provided to the teachers in order to help them orchestrate learning activities more efficiently and to support them in providing appropriate feedback to students (Chounta & Avouris, 2016).

Recently, there is an increasing interest in using Natural Language Processing (NLP) to analyze textual content produced either during learning activities or to assess communication that is facilitated by discussion boards or chat tools (Ferschke, Yang, Tomar, & Rosé, 2015; Yang, Wen, Kumar, Xing, & Rose, 2014). A combination of ML methods, such as NLP and logistic regression or dynamic Bayesian networks, is used in dialogue-based tutoring systems that aim to guide students through adaptive lines of reasoning and support them in conceptualized learning, aiming especially at K-12 education (Albacete et al., 2018; VanLehn et al., 2007)

In the context of educational portals and Learning Management Systems (LMS), ML and data-mining approaches are used to analyze student practices, to assess student performance and provide feedback to learners. The computational methods used for the analysis of learning activities and processes can be summed up in three categories (Suthers et al., 2015):

a) network-analytics methods (usually employing approaches stemming from social network analysis and graph theory) (Chounta, Hecking, Hoppe, & Avouris, 2014; Martínez, Dimitriadis, Rubia, Gómez, & de la Fuente, 2003);

b) process-oriented activity analytics (for example, sequential-pattern mining techniques, time-series analysis, classification and clustering methods) (Bannert, Reimann, & Sonnenberg, 2014; Reimann, 2009; Tarus, Niu, & Kalui, 2018; Ziebarth, Chounta, & Hoppe, 2015); and

c) content analysis using text-mining and NLP methods (Ferschke, Howley, et al., 2015; Mu, Stegmann, Mayfield, Rosé, & Fischer, 2012; Wen, Yang, & Rosé, 2014).

The use of computational methods derived from AI and ML in order to analyze the learning process and to improve the learning outcomes is commonly described by the term "*Learning Analytics*" (Siemens, 2013). Personalized feedback that is informed by learning analytics is offered through student dashboards using visualizations and graph representations (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013).

The report of the Joint Research Centre (JRC), the European Commission's science and knowledge service, published in 2016 (Ferguson et al., 2016) provides an extensive overview of the state of the art with respect to the implementation, adaptation and adoption of learning analytics for education and training. Furthermore, it discusses what actions should be taken with respect to European policies in order to further empower the use of computational methods and tools (such as learning analytics) in

education and consequently enrich educational practices in Europe. This report strongly focuses on learning analytics and not necessarily in the context of OER or K-12 sector but nonetheless, it provides insight with respect to the technological trends in education, and the open issues that we still need to address, both on the policy level as well as on the training ground.

3.2 Recommendation systems

Another application of AI and ML methods in education is in designing and implementing recommendation systems. In recent years, recommendation (or else, recommender) systems are widely used in technology enhanced learning, e-learning and online learning in order to provide recommendations to learners about learning materials and learning content that will assist them in learning efficiently (Verbert et al., 2012). At the same time, it is crucial that these recommendations will be tailored to their personal, individual learning needs (Salehi, Kamalabadi, & Ghouschi, 2013). This is particularly important nowadays with the information overload that learners are facing due to the vast amount of information and content available online. Recommendation systems that aim to support learning activities take into account learner's preferences (based for example on learner's ratings) in order to provide material close to learner's interest and learner's prior activity and knowledge level in order to provide material that will meet the learner's needs (Tarus, Niu, & Mustafa, 2018).

The most common recommendation techniques used in educational contexts, as described in (Burke, 2007) and (Adomavicius & Tuzhilin, 2005), are :

- a) **Collaborative filtering.** The learner receives recommendations based on the learner's similarity with other learners regarding their preferences. Similarity of preferences is computed based on learners' ratings;
- b) **Content-based recommendations.** The learner receives recommendations items that have similar content to the ones the learner visited or rated positively in the past.
- c) **Social-network recommendations.** The learner receives recommendations based on her/his profile and his/her social status.
- d) **Knowledge-based or ontology-based recommendations.** In this case, the learner receives as recommendations items that relate to the learner's needs and items that relate with other items the learner has viewed. Therefore, an ontology-based recommendation system needs to maintain explicit descriptions of concepts in the learning domain that the learner is studying and in addition, the system needs to maintain a representation of the learner's knowledge.

- e) **Hybrid recommendations.** The recommendations are provided using a combination of aforementioned recommendation methods.

According to a recent literature review carried out by (Tarus, Niu, & Mustafa, 2018), ontology-based recommendation systems are the most popular systems used in educational contexts. They have been used in various e-learning scenarios in order to recommend additional reading material to students (Sosnovsky, Hsiao, & Brusilovsky, 2012), to suggest learning goals to learners based on their knowledge state (Capuano, Gaeta, Ritrovato, & Salerno, 2014) or to assist teachers in the design of learning scenarios by recommending appropriate teaching-learning techniques (Mota, de Carvalho, & Reis, 2014).

In the context of OER and open repositories, recommendation systems are used to generate recommendations of learning resources and materials using content features and ratings as well as learner-specific features, such as the learner's history and background knowledge. For example, Ruiz-Iniesta et. al. (2014), proposed a knowledge-based strategy to recommend educational resources from an OER for a computer science major (Ruiz-Iniesta, Jimenez-Diaz, & Gómez-Albarrán, 2014). To do that, they used keywords that were used to describe the domain learning topics covered by the OER. An evaluation of their system suggested that learners were able to find resources faster. Additionally, the recommendations that learners received, were satisfactory with respect to their interest and existing knowledge. Similarly, Shelton et.al. (2010) proposed and evaluated an ontology-based recommendation system ("*Folksemantic*") and a "*recommendation functionality*" that can be used in order to provide personalized recommendations in OERs (Shelton, Duffin, Wang, & Ball, 2010).

Zhuhadar and Nasraoui (2010) proposed a hybrid recommender system that aimed to personalize user experience on the *HyperManyMedia* OER (Zhuhadar & Nasraoui, 2010). This repository contains and offers educational content consisting of online courses, textbooks, multimedia and other learning materials at the Western Kentucky University. The recommendations of learning resources were provided to learners based on their content and with respect to learner's interests.

3.3 Computational tools to support teachers

Recent reports show the benefits of OER use, like for example cost savings for courses using OER material but still demonstrating the same or even better learning outcomes than courses using traditional textbooks. However, they also revealed significant barriers to implementation. Many teachers and instructors are not familiar with OER

and they don't know how to use it, many teachers said that OER take too much time to implement while for some disciplines no good-quality repository with accompanying material, such as tests or homework, is even available⁶.

Thus, the need for computational approaches to support teachers and instructors is evident. In particular, AI and ML approaches aim to support teachers in two ways:

1. By assisting teachers practice.

Such kind of tools use information about student's activity in order to provide teachers with indications or evidence and support them in student's assessment. Teachers can benefit from the accumulation and analysis of students' data traces by receiving input about an individual learner, a learning group or a whole class (Sergis et al., 2017). This information is usually aggregated, processed and visualized using computational approaches and delivered to teachers through teacher dashboards.

Teacher dashboards typically present informative statistics and visualizations of "meaningful" student activity, that is student actions that may indicate either learning or some kind of disruption of the learning process, either on the class or the individual level (Dyckhoff, Zielke, Bültmann, Chatti, & Schroeder, 2012). Teacher dashboards that build on Intelligent Tutoring Systems (ITSs) present information with respect to skills mastery, such as the number of students who have mastered each skill, the number of skills each students have mastered or comparisons between students and mastery levels per skill and so on (Xhakaj, Alevan, & McLaren, 2017). Some dashboards provide feedback to teachers regarding student's practice by comparing the activity of students to either ideal solutions or to other students' practices (Constantino-González & Suthers, 2007). Other, provide "snapshots" of student's work to teachers and textual content coming from student's activity (Voyiatzaki and Avouris 2014). Teacher dashboards allow teachers to be confident in their assessments and the decisions they make (Van Leeuwen, Janssen, Erkens, & Brekelmans, 2015). However, related studies show that the confidence of teachers decreases when their workload increases. When this happens, the dashboards might add workload – especially if they offer visualizations or indicators that need to be further interpreted. To address this issue, some dashboards provide automatic

⁶ <https://www.insidehighered.com/digital-learning/article/2018/11/16/north-dakota-audit-reports-significant-cost-savings-after-oer>

assessments of student's performance (Chounta & Avouris, 2016) or explicit alerts of potential problems (Holstein, McLaren, & Alevan, 2017). Such dashboards aim to assist teachers in adapting to student's needs easier, faster and to support them in deciding whether an intervention (and potentially what kind of intervention) is necessary.

2. By supporting teachers training

In order to assist teachers and help them create learning activities and assess learning outcomes, computational approaches focus on identifying and providing information about the level of difficulty of learning activities and suggestions for more appropriate activities or on exploring teacher performance data to pinpoint the characteristics of effective teaching (Agudo-Peregrina, Iglesias-Pradas, Conde-González, & Hernández-García, 2014; Slavuj, Meštrović, & Kovačić, 2017).

Other platforms, such as eDidaktikum⁷, aim to facilitate teachers training by using learning analytics and competency models to support teachers in acquiring competences necessary for teaching. The platform of eDidaktikum offers tools for teachers to organize materials and learning activities, but most importantly, it offers tools to associate materials with competencies and to track how students' competencies evolve over time. Specifically, eDidaktikum implements a competency model for teacher training to support teachers to track their own practice and learning.

One of the most common criticism of AI and ML approaches is that they are data-driven and not theoretically grounded using pedagogical reasoning (Duval, 2011; Gašević, Dawson, & Siemens, 2015). In addition, their results can be interpreted in more than one way leading to misunderstandings and misinterpretations (Spada, Meier, Rummel, & Hauser, 2005). Current findings (Peña-López, 2016) point towards the need to use technology in order to support and complement - and not to replace - the classroom teacher. Therefore, it is important that any computational approach should be understood and adopted by both learners and teachers.

⁷ <https://edidaktikum.ee/>

3.4 Examples of use of AI and ML technologies in the European K-12 sector

Recent reviews and studies point out that schools rarely adopt or widely use the technology that researchers develop for educational purposes. This gap is attributed either to teachers having other issues of higher priority than the ones addressed by educational technologies or because technology is perceived – or, sometimes, described – as awkward to use (Donaldson, Ntarmos, & Portelli, 2017). A detailed report on educational platforms used in K-12 and their outcomes - published as part of the 2016 JRC Science for Policy Report (Ferguson et al., 2016) - shows that either the “clever” educational tools are rarely used in the classroom consistently or there is little or no information at all about their actual use and outcomes. Furthermore, AI and ML technologies are mostly used “*implicitly*”, that is as part of the backbone of educational platforms. In most cases, AI and ML technologies are considered as a black box and they are seldom visible (if visible at all) to the end-user.

Knewton⁸ – one of the biggest adaptive learning platforms – has been used by more than 10 millions students globally, either as standalone technology or as a component of custom-made local platforms. Its user base is diversified geographically (North and South America, Europe, Africa, Asia, Australia) but also with respect to the education level (K12, Higher Ed, Corporate training, vocational education). Even though, there have been some indications of improvements in students’ retention and academic achievement, there were concerns about the way these indications were obtained (Ferguson et al., 2016). Furthermore, there were concerns and criticism regarding the way corporate platforms like Knewton can be adapted in educational contexts⁹.

A successful example of integrating adaptive and personalized learning spaces into K-12 school classrooms is the European-funded initiative of Go-Lab¹⁰ and its successor, Next-Lab¹¹. Go-Lab is an online experimentation platform that implements virtual labs and that aims to support inquiry learning and to promote innovative and interactive teaching methods in primary and secondary schools. The platform uses learning analytics (in the form of apps) to provide information to teachers and students about their progress and knowledge status. Content is offered in more than 50 languages

⁸ <http://www.knewton.com>

⁹ <https://www.insidehighered.com/news/2013/01/25/arizona-st-and-knewtons-grand-experiment-adaptive-learning>

¹⁰ <https://www.golabz.eu/>

¹¹ <http://nextlab.golabz.eu/>

and teachers can share material and participate in teacher training and other social events (de Jong, Sotiriou, & Gillet, 2014; Gillet, De Jong, Sotirou, & Salzman, 2013; Sergis et al., 2017).

Third Space Learning, an online platform that specializes in math teaching and school leadership, uses AI technologies to support teachers improve their practices. To do that, the platform monitors lessons and provides real-time alerts to teachers regarding their teaching practice. Third Space Learning was used in Pakeman primary school suggesting improvements in students' achievements in Math¹² and also in collaboration with University College London in order to point out what makes a teaching strategy successful¹³.

With respect to measuring learning outcomes, many teachers use specific-purpose applications (such as PearDuck and EdPuzzle, or even the game-like environment Kahoot!) in order to monitor student's achievement and they believe that data-driven computational approaches can lead to innovative and sustainable and, most importantly, positive changes in the classroom¹⁴.

Other initiatives, such as IBM Watson Education along with Edmodo and Scholastic, aim to using AI in order to improve learning outcomes and students' achievement specifically for K-12. The idea is to use AI as personalized, adaptive learning assistants that, on one hand will support students in acquiring the skills as directed by curriculum and, on the other hand will help teachers understand student's individual learning process and accordingly create personalized material¹⁵. It is still however not clear, to the best of our knowledge, how frequently this technology is used in the European K-12 sector and to what end.

The New Media Consortium (NMC) / Consortium for School Networking (CoSN) Horizon Report for 2017 (Freeman, Becker, & Cummins, 2017) provides a detailed roadmap of trending innovative practices and technologies for K-12 as well as their projected short and mid-term impact within the next 5-years. Based on the findings of the NMC/CoSN Horizon report, as well as the JRC Science for Policy report, it is evident that it takes a long time for new technologies to be actually adapted in the classroom. In this sense,

¹² <https://thirdspacelearning.com/blog/secrets-pupil-premium-award-winning-school-pakeman-primary/>

¹³ <https://www.theguardian.com/technology/2016/dec/26/could-online-tutors-and-artificial-intelligence-be-the-future-of-teaching>

¹⁴ <https://www.edsurge.com/news/2016-10-25-not-just-numbers-how-educators-are-using-data-in-the-classroom>

¹⁵ <https://www.ibm.com/blogs/watson/2018/06/using-ai-to-close-learning-gap/>

it is hard to predict how new, “smart” technologies will impact the educational sector in practice. Nowadays, technological breakthroughs are happening too fast for everyone to follow. This however seems not to hold for young people who are exposed in the widespread, everyday use of technology from an early age and who were named for this reason as the “Digital Natives” (Tapscott & Barry, 2009). Nonetheless, the familiarity that students often show with digital media, devices and so on, does not presuppose that they fully understand their operation or the fundamental technological principles on which they operate. Consequently, this means that the familiarity of students with technology can become the source of misconceptions, misinterpretations and, especially in the context of OER, misinformation and misrepresentation. Therefore, on the one hand it is important to integrate technological advancements in the school context and ensure that students’ knowledge of the new digital world moves from superficial to a deep learning experience. On the other hand, the knowledge and experience of students with technology could be used as a challenge for teachers and other educational stakeholders to create the conditions for a new learning paradigm.

4 Challenges

The OER movement along with new opportunities and promising potentials as described in the paragraphs above, also introduced challenges that might potentially hinder the growth and impact of the movement. Such challenges can be the lack of awareness on behalf of content creators on copyright issues; the lack of quality standards and quality control mechanisms that will ensure the appropriateness of open content; and sustainability mechanisms in OER initiatives that will propel them forward (Hylén, 2006). However, here we will focus on challenges and potential pitfalls towards the integration of computational methods. In particular, we will focus on three challenges:

1. Privacy and data protection challenges
2. Technical challenges
3. Pedagogical challenges

4.1 Privacy and data protection challenges

AI and ML methods in educational contexts strongly rely on keeping detailed records of learner's personal (demographics and history data) and activity (as recorded from the learner's activity through some educational platform) data and using this data in order to provide adaptive and personalized support, tailored to the learner's individual needs.

However, the unsolicited and non-transparent collection and use of private data has often been criticized and it has raised both ethical and legal considerations. Especially since the EU established the General Data Protection Regulation (GDPR¹⁶) in May 2018 to provide a common ground for data privacy laws across Europe and to protect individual privacy of EU citizens, we should put emphasis on two directions:

1. Protecting and preserving the privacy of end users. By the term "end users", we refer to the main stakeholders of OER, open repositories and educational platforms: teachers, learners and content creators.
2. Ensuring the ethical collection, use and sharing of data for research purposes under the rules and regulations imposed by GDPR and ethical research guidelines. To that end, researchers need to communicate the purposes of their research and potential implications to stakeholders. Stakeholders should be aware what data is collected, what the collected data will be used for, by whom it will be used, for how long it will be stored, and how they (stakeholders) can maintain control over their data over time. Additionally, stakeholders' informed consent has to be provided before any collection of data takes place.

In order to further ensure the protection of users' privacy, the technical infrastructure that will implement the computational approaches should be carefully designed in terms of supporting use of anonymized data and providing secure storing of user data.

¹⁶ <https://eugdpr.org/>

4.2 Technical challenges

The vision for open and accessible education through the distribution and reuse of learning content advocates for global, cloud-based data infrastructures that will provide centralized access to learning materials and learning resources (such as the Open Discovery Space CIP PSP initiative¹⁷). To the best of our knowledge, this is still an ongoing effort (according to the initiative's website, up to this day, more than 2500 European schools use the school innovation toolkit) that aims to provide access to shared content as well as to train stakeholders (mainly teachers and school leaders) in designing innovation plans, designing educational activities and producing and assessing educational content.

However, at the same time these centralized repositories should also facilitate user experience and practice by integrating “intelligent” support for multiple aspects of user activity, such as personalization of the learning environment, adaptive instruction, personalized recommendations, and tailored feedback. A potential challenge may arise from the complexity and high cost of maintaining systems that can provide computational power for such demanding tasks. To that end, we could also consider cloud-based solutions that will choose computational approaches with respect to efficiency from an open and centralized repository of AI and ML tools. An example of such a centralized repository is the LearnSphere initiative¹⁸ that combines educational data from multiple data sources and analytical methods from various online workbenches.

4.3 Pedagogical Challenges

OERs provide the opportunity for learners to gain access to high-quality learning materials that they can access from their own private space. This empowers the individual learner but at the same time it may raise pedagogical challenges regarding social aspects of learning and the role of the individual as a member of a community of practice. It has been argued that in OERs individual learners may “*find themselves adrift in an ocean of information, struggling to solve ill-structured problems, with little clear idea of how to solve them, or how to recognize when they have solved them*” (Shum & Ferguson, 2012). By using AI and ML methods to support adaptation and personalization, we may be enforcing the isolation of individual

¹⁷ <http://www.opendiscoveryspace.eu>

¹⁸ <http://learnsphere.org/>

learner and put community-building practices at risk. Therefore, our computational approaches should on one hand focus on personalization and adaptation to address the learner's needs but on the other hand we should consider scaffolding communication and fostering collaboration and the acquisition of social skills that will empower learning in a social arena.

Another pedagogical challenge that we have to address is how to support content creators in designing high-quality content and content distributors in locating and accessing high-quality content. To address this challenge, it is crucial to identify what we mean by "*high-quality*". In short, a good OER should follow the following guidelines (Kawachi, 2014; Shank, 2013):

- a. It should be easily discoverable, accessible in multiple formats and multiple locations, and to include transcripts/subtitles if needed;
- b. It should provide accurate and relevant information, without errors, clearly described content and free-standing (not assuming knowledge of other resources);
- c. It should be free of copyright and it should not require any license for educational reuse or modification/adaptation of the materials
- d. It should be easy to modify, easy to navigate and of good production quality
- e. It should provide scaffolding and encourage active learning and opportunities for practicing and testing students' understanding of the material.

In order to assess relevance of information, semantic search approaches such as concept matching and natural language processing have been widely used. Similarly, accessibility guidelines that were originally developed to ensure accessibility of web content (like for example, the Web Content Accessibility Guidelines 2.0, WCAG 2.0¹⁹) are now used to assess whether OER content is easily accessible. Furthermore, OER-specific search engines have also been brought together to support stakeholders in retrieving good-quality material.

However, we should keep in mind that quality of content largely depends on the needs and perceptions of the end-user. In this sense, quality assurance and validation cannot come from a top-down approach that will perform a centralized quality control ²⁰. On the contrary, such quality control should take into account the end-

¹⁹ <https://www.w3.org/WAI/standards-guidelines/wcag/>

²⁰ <http://www.oerafrica.org/healthoer/AfricanHealthOERVisionStatement/tabid/955/Default.aspx>

users, engage them proactively in providing feedback and suggestions for enhancements, support them in adapting the content themselves and sharing it with the community. In other words, quality control can be envisioned as a bottom-up approach, empowered by big data, AI and ML technologies and crowd-sourcing models.

5 Conclusion

In this report, we provide an overview of the most prominent AI and ML practices used in educational contexts focusing on OER and educational portals aiming to support K-12 education. To that end, we provided definitions and descriptions of the terms that were referenced in this paper, a short historical overview of AI and ML in education and an overview of the goals and common practices of the use of computational methods (AI and ML) in educational contexts.

The benefits of adopting AI and ML computational methods in educational portals and OERs is threefold:

- a) **Delivering the tools to stakeholders** to choose effectively and efficiently for appropriate resources and content that meets their standards;
- b) **Allowing the adaptation and personalization of learning content** and also the adaptation and personalization of the learning environment itself in order to address the characteristics of the individual learner;
- c) **Providing the means to learners to gain and maintain an overview of their practices** and gain control not only over the resources they are using but also with respect to their activity and performance through monitoring and adaptive feedback.

Future efforts should support local structures and directives to move forward with the integration of computational approaches to existing OER and educational portals. As aforementioned, evidently there is a need for cloud-based, large infrastructures that will offer centralized access not only to learning materials but also to user data and computational tools. An “intelligent” infrastructure will support the scaling of computational methods in OER and educational platforms, bring together approaches from different educational contexts and methodological traditions and will enable the emergence of new technological advances.

However, in order for such an infrastructure to be successfully and consistently implemented and used, there is a need for a methodological framework that will promote and orchestrate stakeholders to undertake common actions that would

support the integration and use of AI and ML in OER and educational portals on a large scale. This will require the support of different entities, such as educational and academic institutions that will provide quality assurance with respect to the pedagogical value and benefits and policy makers on a national and EU level. This is a crucial issue since attempting to create a common infrastructure that would allow sharing of learning materials, learning data and analytical tools across different educational settings and beyond national borders would entail not only pedagogical and technological but also legal and ethical challenges.

5.1 Looking ahead: Taking the next step to promote AI and ML integration in European schools

In order to achieve successful integration of AI and ML technologies in the classroom, we first and foremost have to bridge the gap between the rapid research and technological advancements in AI and ML and the slow – or even no – adaptation of such technologies in schools. One step towards that direction could be:

- a. to support stakeholders (teachers, students, school directors, policy makers) to familiarize with AI and ML research;
- b. to demonstrate to stakeholders that AI tools are not black-boxes but they are actual products of rigorous scientific research; and
- c. to carry out long-term initiatives (such as hands-on workshops) where teachers and students will be guided how to properly adopt AI and ML technologies in their classrooms without disruptions.

A second step would be to involve stakeholders when designing cutting-edge computational tools. It is a common feeling between teachers and a valid concern that *“there is a big disconnect ...between the technology we receive versus the tech we want”* and that *“it’s not about the data, but how do we apply it. The reason why this technology sucks is because we don’t do good design”*²¹. Therefore, in order to address such concerns, it is necessary that we involve stakeholders (teachers, school leaders, students and policy makers) when designing educational technology. This can be achieved by using a socio-technical participatory approach where technology experts along with stakeholders identify prominent needs and requirements and then work together to develop a solution for

²¹ <https://www.edsurge.com/news/2018-09-26-what-can-machine-learning-really-predict-in-education>

addressing these needs. A similar approach was followed by the European-funded project SHEILA²² that aimed to build a policy development framework that would promote formative assessment and personalized learning.

In the case of using AI and ML to facilitate OER in the European K-12 sector, we envision a project that will have as a purpose to create complementary sociotechnical-pedagogical prototypes and designs-in-practice that help a) learners to become critical-constructive and reflective *thinkers* in cultures of sharing and participation and b) teachers to become the “*process designers*” of the *critical thinkers*. In a digital networked world, teaching is not only seen as the creation of conditions for enabling learning; most importantly, teaching is creating conditions for learning through discovering, understanding, and critically assessing material that can be found openly. Borrowing the acronym from the Bring Your Own Device movement (Bennett & Tucker, 2012) – that is, BYOD – and that it refers to workers who use their own personal devices in their workplace, we envision the BYOR movement: *Bring Your Own Resources*. In this context, students are expected to retrieve relevant learning resources for meaningful activities designed by teachers, who are also responsible for ensuring that that the learning objectives have been met. The role of AI and ML in this project would be threefold:

1. to support students in retrieving appropriate learning materials and provide feedback that could be used for improvement;
2. to assist teachers in assessing the students’ materials and provide further suggestions to students with respect to quality control;
3. to implement a crowd-sourcing based infrastructure that will communicate students and teachers findings and suggestions in order to create a bottom-up quality control approach that can be shared and re-used from stakeholders with similar needs.

We foresee that such an effort could substantially promote the vision of open education where learners can access freely resources and practice competencies that will help them acquire the skills needed for functioning in the digital age, teachers can ensure that the learning objectives are achieved and that OER end-users can contribute actively to setting the bar with respect to quality control and standards.

²² <http://sheilaproject.eu/>

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