Quaderni di Comunità

Persone, Educazione e Welfare nella società 5.0

Community Notebook

People, Education, and Welfare in society 5.0

n. 2/2023

TEACHING ENHANCED LEARNING FOR ENGAGING AND INCLUSIVE LEARNING

Edited by

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eurilink
University Press

Iscrizione presso il Registro Stampa del Tribunale di Roma
al n. 172/2021 del 20 ottobre 2021

Eurilink University Press Srl
Via Gregorio VII, 601 - 00165 Roma
www.eurilink.it - ufficiostampa@eurilink.it
ISBN: 979 12 80164 69 8
ISSN: 2785-7697 (Print)

Prima edizione, novembre 2023
Progetto grafico di Eurilink

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4. APPLICATION OF LEARNING ANALITICS IN EUROPEAN GENERAL EDUCATION SCHOOLS: THEORETICAL REVIEW[1]

by Aleksandra Batuchina[*], Julija Melnikova[**]

Abstract: *The increasing use of technology in education goes hand in hand with the areas of learning analytics and artificial intelligence in education, with a particular focus on how data can be used to improve the teaching/learning process. In the last decade, there has been a lot of discussion in the European Union about data and evidence-based education, school management and management of the education system. The data is used to make systematic decisions on education policy at the national or regional level, to prepare school improvement plans, to consider the educational processes of a class or a specific student. Artificial intelligence and learning analytics are becoming the most popular ways to analyze collected data in digital learning environments to support teachers and learners in their learning. However, it is emphasized at the European level that almost no research has been found that would have answered the question of how learning analytics could be applied in general education schools in order to improve schools' activities. The purpose of the scientific essay is to present literature review on learning analytics research and to explore examples of the application of learning analytics in general education. As a result, this essay provides a comprehensive literature review covering these aspects. Searching of the articles were performed through Google Scholar, EBSCO Research Database and Scopus*

[1] Accettato Febbraio 2023 - Pubblicato Agosto 2023.
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Preview. In general, more than 157 article dated from 2006 till 2022 on the topic of learning analytics were analyzed. Research findings reveal that learning analytics as tools should not only include effective technological and pedagogical solutions, but it is important to consider many contextual and human factors in order to answer the questions of why and how they will be used, as well as by whom and in what context.

Keywords*:* Learning analytics, European schools, educational technologies in schools

Introduction

Technological progress in the world and in Europe encourages the use of artificial intelligence in various fields. One of the most important goals of its application in education is personalized learning providing guidance or support to specific students based on their learning level, preferences or personal characteristics (Hwang *et al.*, 2020). The resolution of the European Parliament (European Parliament, 2021) indicates that artificial intelligence in the education system should contribute to the most individualized education possibilities, offering learners personalized teaching and learning methods that match their strengths and weaknesses, and didactic material adapted to their particularities, while maintaining the quality of education and integrating the principles of the education system. Learning analytics can contribute to this goal.

Of all the applications of artificial intelligence in education, it is the analysis of learner data that has the greatest capacity to provide useful insights needed to make decisions about resource allocation and to improve the quality of student learning (Long, Siemens, 2011). Learners and teachers can benefit from the automatic feedback of AI-based data analysis to reflect on their learning process and progress. Learning analytics leaves the decision-making to the human, but backs it up with automated data analysis using AI techniques.

In 2011 emerging as a distinct scientific field, learning analytics has developed rapidly, and its early adopters continue to develop and implement new tools (Ferguson et al. 2019). As an interdisciplinary and multidisciplinary field, learning analytics includes research and practice in education, psychology, and data science (Tsai *et al.*,2018; Nouri *et al.*, 2019). According to Nouri et al. (2019), the report of European Commission Working Group on Digital Skills and Competences (ET2020) draws attention to learning analytics that can "contribute to training and the quality of learning and the modernization of European education systems" (Nouri et al. 2019, p. 10). In addition, ET2020 is encouraged to develop relevant capacities and collaborate on research projects.

In response to the ET2020 call, various collaborative groups in European countries have been assembled (Ferguson et al.2015; Nouri et al.2019). E.g., Stockholm University (Sweden) Learning Analytics Research Group, Danish Center for Big Data Analytics Driven Innovation (DABAI), learning analytics working group initiated by the University of Amsterdam (Netherlands), learning analytics community with a proven track record was recently developed in Estonia etc.

Two approaches to the application of learning analytics in general education are currently distinguished in Europe (OECD, 2021 a; OECD,2021 b.). Based on the first point of view, learning analytics should be applied in the formation of educational policy, management of educational institutions, improvement of the training process (Agasisti, Bowers, 2017; cit. OECD, 2021a). Based on the second approach, it is more difficult for schools in education to take full advantage of the learning analytics that higher education institutions use effectively. According to proponents of this approach, comprehensive, multi-layered analytics are necessary for general education schools as a system with different levels of data that would provide school leaders and other stakeholders with comprehensive and reliable feedback on school processes. Such analytics could help capture, analyze and use organization-wide data, allowing school leaders to monitor and (partially) influence organizational processes in order to better respond to the needs of students, teachers, and parents and external policy expectations (Sergis, Sampson, 2016; cit. OECD, 2021a). Considering to this, it is proposed to include micro-level (monitoring and evaluation of the learning process and learners' activities), meso-level (curriculum planning, pedagogical staff management, teacher qualification improvement) in the learning analytics system, and macro-level (accountability of school founders, management of infrastructure and financial resources and learner data). However, it is emphasized that almost no research has been found that would have answered the question of how education stakeholders could apply learning analytics to improve school's activities (Jimerson, Childs, 2017; cit. OECD, 2021a).

The European Commission report "Evidence from Research on the Application of Learning Analytics: Impact education policy "(Vuorikari et al. 2016) discusses several issues related to learning analytics. In particular, there is a large gap between learning analytics tools, their application to improve education and possible benefits of learning analytics, which are emphasized in the world scientific research, they are also emphasized by the developers of learning technologies. Current learning analytics initiatives focus on the supply side – the development of tools, data, models and prototypes. Less attention is paid to the need to analyze how analytics relate to education, what changes school administrators, teachers, and students expect to see learning analytics tools help in day-to-day in the training process. In addition, learning analytics technologies are mainly focused on the analysis of student dropout issues, with less emphasis on pedagogical processes and practices. Another problem with current learning analytics actualizes the search for their validation methods, i.e., how to determine if these tools meet their intended purpose and have a positive effect on the teaching/learning process. This one the issue is partly related to the lack of long-term studies with a target to document the positive impact of learning analytics.

Taking everything into consideration, the current essay aims to discuss the possibilities of integrating learning analytics into general education theoretically emphasizing the benefits of learning analytics tools powered by artificial intelligence. The purpose of the scientific essay is to present literature review on learning analytics research and to explore examples of the application of learning analytics in n general education. As a result, this essay provides a comprehensive literature review covering these aspects. Searching of the articles were performed through Google Scholar, EBSCO Research Database and Scopus Preview. In general, more than 157 article dated from 2006 till 2022 on the topic of learning analytics were analyzed. Moreover, research findings reveal that learning analytics as tools should not only include effective technological and pedagogical solutions, but it is important to consider many contextual and human factors in order to answer the questions of why and how they will be used, as well as by whom and in what context.

1. Digitalization of education

Digital technologies are changing different areas of people's life such as communication, social life, opportunities for cooperation, and are forming new life habits. These changes also affect education. Even already in 2014 research predicted that in a decade about two-thirds of general education students in Europe will be learning, fully or partly, in a digital-based learning environment (Wang, Decker, 2014). Researchers have hypothesized that portable computing devices and evolving educational technologies (for example: smart classrooms, smart learning environments, etc.) will foster even more rapid digitization of education in the nearest future (HarCarmel, 2016). Therefore, the content, forms, methods, roles of educators and learners and interactions in the teaching / learning process will have to change over time (Hollman *et al.*, 2019).

In recent years, the issue of digitization of education in Europe has become even more relevant. On the one hand, the COVID-19 pandemic situation has greatly accelerated the digitization of education. An unprecedented hasty experiment with school systems took place during the pandemic all over the Europe with hundreds of millions of learners moving to a digital learning environment (Kalim, 2021). As a result, digital technologies have become part of the teaching/ learning process and, according to researchers, their use has been proven to be crucial in ensuring better education for learners during a pandemic (Kurvinen et al., 2020). On the other hand, target groups in education - students, parents, teachers and school leaders - are increasingly using technology for a variety of educational purposes, for instance, informing students about their achievements in an e-diary environment (Wang *et al.*, 2016). Thus, these processes encourage even more rapid digitization of education.

The scientific literature (Hollman *et al.*, 2019) increasingly raises questions about how digital technologies change education, how they affect participants in education, how to use the advantages of technology to improve the quality of education, how to overcome technology-related challenges in education, and so on. One of the main factors driving their application in general education is the findings of research showing that teachers and students in general education schools show a high level of support for intelligent learning systems (the study involved the following learning experience platforms: ALEKS, Cognitive Tutor, Khan Academy, edX and Coursera) (McHugh, 2015). In addition, these systems contribute to the development of the concept of evidence-based education (Khine, 2018) by providing data-based feedback and the opportunity to analyze and improve the teaching/learning process.

The ever-accelerating application of technology in education is parallelly associated with the fields of learning analytics and artificial intelligence in education, with a special focus on how data can be used to improve the learning process. When teaching/learning takes place in digital technology-based learning environment, a certain interaction of the learner with the digital tool used for learning is inevitable, the specific learning experience of the learner is being accumulated, which creates large flows of digital data (HarCarmel, 2016). These data describe the individual learning activities of users of learning systems or the interactions of learners in group learning (McHugh, 2015).

2. Big data in education

The emergence of big data in education is associated with two main trends of the digital era (Fischer, 2020):

- The data systems of educational institutions are increasingly digitized, resulting in a lot of standardized information. E.g., Data systems are designed to store and manage student information (such as demographics) and academic records (such as class enrollment). Such systems archive data, and their digitization enables the management and analysis of that data.

- Learning behaviors, which were difficult to capture in classrooms, can now be partially captured by learning management systems. Most often, learning management systems are used by teachers to distribute educational materials, manage student assignments, and communicate with students. These systems generate thousands of data points for an individual student. In addition, diverse digital learning environments not only enrich pedagogical possibilities, but also collect students' digital footprints.

Digitization of education, online activities of educators and learners create a huge source of digital data. The data is so large that it can exceed the computing and data processing power of a single computer; thus, data processing often requires computer clusters (Hesse *et al.*, 2015). The sources of data are diverse: logins to various digital applications, web browsing data, social media data, geo-located images and even audio data (McHugh, 2015). Thus, high volume, speed and variety are considered the main characteristics of big data.

Although big data in education is still a relatively new phenomenon, the value of information obtained from big data is unique. From a research point of view, this is a promising opportunity to contribute to the personalization of student learning, as well as to the formation of educational policy.

The integration of big data aggregation technologies into digital education tools has a number of advantages for education (Har Carmel, 2016):

- Personalization of learning: big data can lead to personalized learning, which goes beyond adapting pedagogical methods or tasks to the specific learning needs of students, but enables learners to design their own learning based on how they learn, what are their learning needs, goals, aspirations and even according to the socio-cultural background of the learners (Mayer-Schönberger, Cukier, 2014).

- Adaptive learning: adaptive learning systems can continuously collect and interpret student data, change the direction and environment of students' learning, taking into account their needs and abilities (Dumon, 2014).
- Accurate assessment: big data makes it possible to monitor students in their learning process, so it is possible to apply new assessment methods that more accurately assess student achievements (Polonetsky, Jerome, 2014).
- Effective feedback: Big data can help ensure a more reasonable and effective feedback cycle - students receive feedback in real time and based on their real contribution (Weber, 2015).
- Learning prediction: student behavior, skills and learning outcomes can be predicted based on the analysis of student activities on digital platforms. This is also important for teachers - they can pay more attention to students with specific gaps (Charlton *et al.*, 2013).

Traditionally, schools have been empowered to "govern, administer, discipline, form, care for and empower students through a variety of pedagogical methods" (Pykett, 2012). As education becomes more and more data-driven, a larger part of the school functions i.e. teaching, learning and assessment can be "taken over" by technology (Burch, Good, 2015). On the other hand, this trend shifts the responsibility for data into the hands of for-profit organizations that now have the ability to collect, store, and process it. Therefore, the increasing movement of big data and unclear questions of data "ownership" raise concerns about data security, privacy protection, and the ethical limits of access to personal digital data.

3. Big Data and Learning Analytics

In response to the emergence of big data in education, learning analytics has become a rapidly developing field that includes learning analytics as a research field and learning analytics as a practical application field (Macfadyen *et al.*, 2014). The focus on learning data analysis has opened up a whole new field of educational research and provided an opportunity to reconsider how this type of analytics can help improve the content of a teaching/learning subject and improve the teaching and learning process in a technology-based learning environment (Zilvinskis, Borden, 2017). Learning data analytics has become a new practice concept in educational institutions. According to Czerkawski (2015), this is a new and promising method that expands practitioners' knowledge about the teaching and learning process.

A widely used definition of learning analytics in the scientific literature is: "The collection, analysis, and reporting of data about students and their contexts to understand and optimize learning and the environment in which it occurs" (Long *et al.*, 2011). This is an official definition from the Society for Learning Analytics Research (SoLAR) and emphasizes learning analytics pursuit of using data to comprehensively understand and improve educational systems.

Based on analytical methods from various fields (e.g., computer science, data mining, machine learning, statistics, sociology, psychology, etc.) learning analytics is being integrated into adaptive learning systems, computer-based learning, intelligent learning systems (Romero, Ventura, 2013). Learning analytics not only analyzes student demographics, learning outcomes and certain psychological indicators, but it is capable of analyzing “small” data, e.g., number of computer mouse clicks, number of attempts, learning browsing patterns, participation in online chats, forum chats, visual and facial reactions (Bousbia, Belamri, 2014). All of these data are valuable to educational researchers and practitioners, as they enable the linking of learning activities and social interactions, which in turn lays the foundation for a new paradigm of learning assessment and pedagogy (Baker *et al.*, 2021).

Learning analytics as a field of research is related to related fields such as: data analytics, educational data mining, qualitative ethnography (Chen, Zou, 2020). The development of learning analytics as a field of practice has been driven mainly by political and economic factors.

The beginning of the development of learning analytics as a field of practice is associated with predictive modeling systems. Political and economic priorities are shaping education sectors around the world. E.g., in many countries, higher education funding models are strongly influenced by the number of students who successfully graduate. Therefore, education policy makers and administrators have seen the potential of analytics to increase student retention through predictive modeling and early warning systems (Siemens, 2013). In parallel, there has been growing interest in predictive analytics and general education to improve student academic achievement (Bowers *et al.*, 2012; Singh, 2018). Using analytics to support student retention and other priorities of higher education institutions has given rise to the academic branch of analytics (Campbell, 2007), a field that has strongly influenced learning analytics. The emergence of academic analytics has led to close ties between the education community and the higher education information technology leadership community (e.g., project "EDUCAUSE").

The development of the practical application of learning analytics has been greatly stimulated by the increased interest in educational digital technologies. The rapid deployment of learning management systems (LMS) in higher education has led to the generation of large amounts of data (Ferguson, 2012), which has led to research into the use of log data recorded by LMS's and to the development of reporting systems (known today as dashboards) based on weighted information visualization and relatively simple data analyses. methods (Jovanovic et al. 2008; Rienties et al. 2018). These technologies have offered useful solutions for the academic community, while also encouraging the involvement of other stakeholder groups such as instructional designers and educational/learning technology developers (Weller, 2020).

It is important to note, that artificial intelligence and learning analytics aim to improve learning processes by systematically processing teaching-related data and providing guidance to teachers and learners. Researchers in artificial intelligence and learning analytics analyze cognition, motivation, influence, language, social discourse, and other issues based on data derived from digital learning environments. Therefore, the possibilities of integrating artificial intelligence and learning analytics are of particular interest in learning environments such as: adaptive learning systems, intelligent learning systems and open educational resources (Mandinach, Gummer, 2016). These technologies aim to inform teachers and learners, as well as other stakeholders, as effectively as possible, and to encourage their interaction and collaboration, and contribute to improving of the quality of teaching / learning (Holstein *et al.*, 2019).

As technology develops, innovations such as computer-based learning environments, adaptive learning systems, intelligent learning systems and massive open online courses (computer-based learning environments such as adaptive learning systems, intelligent tutoring systems, and massive online open courses) (Essa, 2016). One of the main factors driving the adoption of these technologies in general education has been the increasing focus on standardized tests and the need for schools to demonstrate improvement in these tests in order to receive funding. This phenomenon started in the United States and the United Kingdom, but later spread throughout the world (Lingard, Lewis, 2016). Even without the financial support typical of the higher education sector, teachers and students have shown strong acceptance of these technologies (Ferguson, 2012). Large platforms such as ALEKS, Cognitive Tutor, Khan Academy, edX, and Coursera have grown to hundreds of thousands or millions of users. Learning analytics research has identified how to use data to make these platforms more effective:

- improving learners' knowledge, knowledge assessment processes, improving the organization of training programs and their content (Ritter *et al.*, 2016);
- improving schedules of learning activities according to human memory models (Settles, Meeder, 2016);
- embedding complex evaluations of intervention strategies (Li *et al.*, 2018);
- determining which interventions are more appropriate for different groups of learners and in different contexts (Sales *et al.*, 2018).

In recent years, artificial intelligence and learning analytics have been integrated by an increasing number of digital tools, both commercial, such as MS Teams, Google Classroom, iSpring Learning, and open source, such as Moodle, and other platforms, which have been designed for various educational sectors. Today learning experience platforms based on artificial intelligence and integrative learning analytics tools are seen as one of the most effective tools to make it easier for learners to learn and easier for teachers to teach (Rienties *et al*, 2018).

4. Learning analytics benefits for school community

Contemporary research and practice of learning analytics in general education demonstrate its value in addressing issues related to learning quality, identifying at-risk students, and reducing exclusion (Sclater, Mullan, 2017). In addition, learning analytics proves to be a tool for monitoring and improving the performance of the school as an organization, as well as for monitoring and developing the organizational capacity of the school (Ifenthaler *et al.*, 2019).

Knowing what the data is used for and how to analyze it is essential to the benefits of learning analytics. According to the purposes of data use, learning analytics can be divided into:

- summarizing and descriptive - these are detailed insights at the end of a certain learning stage (e.g., study year, semester), most often comparisons are made with previously defined reference points or standards (benchmarks);
- formative - which is used for real-time evaluation purposes. These analytics provide continuous feedback/data that helps improve processes through direct interventions in “real-time”;
- predictive and indicative - which allows predicting the probability of outcomes and planning future interventions, strategies and actions on that basis (Ifenthaler, 2015).

Potential stakeholders for learning analytics include students, teachers, classroom teachers, school leaders, and educational administrators.

First and foremost, learning analytics tools benefit students. The main goals of learning analytics are to improve academic achievement rates and help students develop greater responsibility for their own learning activities (Siemens, 2011). Learning analytics tools can direct students to their individual learning paths (Hylen, 2015), provide students with information about the gap between their current and desired learning outcomes (Admiraal *et al.*, 2017), encourage students to learn (Abo *et al.*, 2016), assess each student's level of competence and provide feedback in a compact and clearly laid out manner (Ebner, Schön, 2013). Learning analytics tools allow students to take control of their learning by informing them of their engagement in learning activities and helping them to determine what they need to do to achieve their educational goals (Dehler *et al.*, 2011; Davis et al. 2018). Learning analysis tools support self-regulated learning and help students self-assess and adjust learning strategies in order to increase achievement of goals (Papamitsiou, Economides, 2015). In this way, learning analytics tools can expand and improve learner achievement, motivation, and confidence by providing students with timely information about their and their peers' performance, as well as suggestions for activities and content that could help address identified knowledge gaps (Siemens, 2011).

The second group of stakeholders are teachers who want to analyze their classroom situations in more detail (Khine, 2018). Learning analytics tools allow teachers to form timely and meaningful assessments of ongoing learning activities. Learning analytics tools increase teachers' understanding of student achievement (Papamitsiou, Economides, 2015; Guo *et al.*, 2017), potential misconceptions (e.g., guess correct answers) (Papamitsiou, Economides 2015), approved curricula and training) effectiveness of strategies (Meyers *et. al.*, 2016). Learning analytics can inform teachers about the quality of instructional content and the impact of teacher-proposed activities and the effectiveness of their assessment process (Jivet *et al.*, 2018). Teachers can use this data to learn how students are learning and what their main strengths and weaknesses are. Based on fine-grained evidence, such as the level of computer-based assessment skills, engagement in activities, etc., teachers can also make important pedagogical decisions. This fine-grained data is also important for monitoring changes in performance (Pardo *et al.*, 2016). Teachers can effectively use detailed information about students' knowledge gaps in different subject areas. Information about a student's strengths and weaknesses could be used by the teacher to plan interventions where the student needs help moving forward. In this way, learning analytics tools can help teachers highlight students who may need extra help (Siemens, 2011; Admiraal *et al.*, 2017; Hylen, 2015) or reflect on different ways to encourage students to learn further (Admiraal *et al.*, 2017). On the other hand, learning analytics tools can assist teachers in considering the design and development of new course programs (McKay, 2019) and help them improve the quality of digital textbooks and instructional materials (Mouri *et al.*, 2018). Many educators strongly believe that, when used properly, learning analytics can be an essential tool for closing the achievement gap, increasing student success, and improving the quality of education in the digital age (Khine, 2018).

Learning analytics tools are a potential way to ensure quality and greater efficiency, which is critical for any educational institution. Using learning analytics tools, school leaders can gather data to help make informed decisions at the school-wide organizational level. School leaders are therefore another stakeholder group that benefits from learning analytics tools. School leaders focus on school and classroom performance and use that data for school performance evaluation/evaluation purposes (Khine, 2018). School leaders can use learning analytics tools to predict and design different teacher effectiveness and the most appropriate professional development opportunities to offer to a particular teacher (Pardo *et al.*, 2016). Learning analytics tools allow school leaders to improve the flow of knowledge throughout the organization (Siemens, 2011), make decisions about educational reform, better understand the factors that influence learning achievement, and allocate resources based on accurate, up-to-date information about activities within the organization. In this way, learning analytics tools provide school leaders with clear guidance on how to improve processes in schools (Mouri et al. 2018), provide continuous feedback and systematic support to school leaders (Long, Siemens, 2011) and enable effective school management (Sergis, Sampsonas, 2016). Learning analytics tools provide school leaders with aggregated data sets related to standardized assessment scores that are typically compared to similar schools or data that measure the impact of specific school strategies (Meyers *et al.*, 2016).

Stakeholders outside the school are also interested in learning analytics results. In most countries, government institutions annually analyze the results of students' national examinations. Learning analytics tools allow them to compare schools and illustrate the potential contribution of information collected and analyzed using learning analytics tools to promote continuous improvement of schools' educational processes (Andrade, Silva, Camanho, 2017).

The last but not the least stakeholder group is the parents. Learning analytics tools provide parents with ongoing information about their children's progress and results, allow them to compare their children's performance with that of other students in the class, and monitor whether their children are consistently learning.

5. Limitations of learning analytics

Despite the potential of learning analytics, there is considerable hesitation and skepticism about the challenges of its application in education, as well as unanswered questions about how its use could contribute to the desired learning outcomes (Zeide, 2017). Stakeholders face issues such as: transition from traditional data analysis to learner-centered analytics, working with diverse data sets in different environments, technological barriers, ethical issues of data collection and use, etc.

For purposeful and effective application of learning analytics, it is necessary to clearly distinguish it from statistical activities related to traditional analysis and data mining (Siemens, 2011). Teachers should understand that learning analytics is not limited to these activities, but goes beyond them, as it includes the aspect of human judgment: understanding information, making a decision based on data and implementing a certain action/ intervention based on it.

In order for learning analytics to properly address the needs of learners, it is important to ensure that the focus of the data is on the learner's perspective (Ferguson, 2012). Such data as, for example: student activity, confidence, motivation, satisfaction in the learning process contribute to the indicators that reveal the quality of learning. Teachers should be prepared that the shift towards learning analytics may require fundamental changes in teaching/learning methods in order to generate, collect and properly analyze data (Reyes, 2015).

The process and principles of learning analytics should be clearly understood by the learners themselves (Clarke, Nelson, 2013; Ferguson, 2012). In this sense, teachers and schools should design the teaching/learning process and pedagogical models in such a way that students can better understand their learning behavior and outcomes (Ferguson, 2012).

As learning analytics collects data from a variety of sources, such as task performance, task assessment, student register (e.g., socio-demographic) data, library use, etc., researchers will be challenged to develop methods for working with datasets that can be applied in various environments (Siemens, 2011). Ideally, a system should be created to aggregate this data and provide access to datasets with analytics and visualization capabilities, visually and clearly accessible to the end user, enabling information sharing with stakeholders. Siemens (2011) also notes that there is a gap between research and practice when it comes to managing and sharing information, tools and datasets. Close collaboration between software developers, researchers and practitioners should be ensured to achieve understanding of social stakeholders, which in turn will help to achieve the result.

Learning analytics also raises new ethical issues that need to be addressed. Emerging technologies such as e.g. geolocation tracking and biometrics, make it possible to collect a variety of data beyond learning activities. If learners feel that their privacy is being compromised, they may not want their personal data to be used for research and analytics. In addition, in some cases it is not entirely clear who owns the data – the person, institution or external entity that is the owner of the data collection tool (Greller, Drachsler, 2012).

Unlike traditional data analysis and research approaches, virtual environments do not currently have defined guidelines for researchers on how to use data after obtaining consent. There are also no rules for learners regarding the retention of analytics records. There are also no established guidelines for preserving the anonymity and confidentiality of data (Ferguson, 2012; Greller, Drachsler, 2012). For these reasons, there is a need for an ethics manual that clearly defines data management, data ownership issues, and a clearly defined privacy policy in order to protect data from misuse.

Implications

Although artificial intelligence is increasingly penetrating various fields, including education, providing many options for its application, a unified and clear policy on artificial intelligence, especially in aspects of its application outside higher education institutions, is still lacking. Many recommendations and guidelines have been prepared in the European Union, and various initiatives are more focused on further development and application of artificial intelligence and the ethical dimension of this activity.

The science of learning analytics, which has only been around for a decade, is getting more and more attention from developers who have discovered how to apply it in education. However, the offer of learning analytics so far eliminates the needs and expectations of actors in the field of general education, because their involvement in the processes of creating learning analytics is missing. More attention is drawn on its application in higher education. Higher education institutions can use a wide range of learning analytics tools based on the documents governing the application of learning analytics. Nevertheless, in primary and secondary education, after the introduction of various educational technologies, and the creation of new classroom-oriented technologies, the possibilities of learning analytics to support learners and diagnose their learning progress in a pre-university context were revealed. However, what is missing is both a clear policy on learning analytics at the pre-university level as well as research that would reveal how, for example, national and local education policy makers could apply learning analytics to improve school performance.

The European resolution "Artificial intelligence in the education, culture and audiovisual sector" (2021) emphasizes the importance of developing basic digital and artificial intelligence skills, expanding teacher training opportunities, embedding education in large risk in the regulatory area of artificial intelligence systems, given the particularly sensitive nature of student and other learner data. It is emphasized that teachers' education plays a central role in the process, which is multifaceted, especially in early childhood, when the most important competencies are acquired that will allow students to develop throughout life, such as personal relationships, empathy and cooperation, and therefore teachers will not replace any artificial intelligence or related technology. Also, data protection issues are emphasized, which, unlike traditional data analysis and research access, are not yet sufficiently regulated. Therefore, an ethics guide is necessary, which would clearly define data management, their ownership issues, privacy policy, in order to ensure that the data is protected and not misused.

In conclusion, it can be said that the benefits of applying artificial intelligence in European education will depend not only on the artificial intelligence itself, but also on how teachers use it and will apply learning analytics to digital learning environments to meet the needs of students and themselves as teachers and other stakeholders (Reyes, 2017; Artificial intelligence in the education, culture and audiovisual sector, 2021). The following limitation threats can be distinguished:

- The application of artificial intelligence in education offers many opportunities and tools to make learning more innovative, inclusive and effective when implementing new artificial intelligence and learning analytics tools that can individualize and personalize training, but it is necessary to emphasize that their availability must be ensured for all social groups guaranteeing equal opportunities to use them and leaving no one behind, especially the disabled.
- A wide variety of data is generated in the general education process, but detailed data on students' learning achievements, their demographics, etc. not easily accessible to people who need it most - teachers, heads of educational institutions and support specialists. By the way, existing data do not always clearly reveal the situation so that school staff can accurately identify and locate teaching and learning problems and the best ways to solve them.
- There are many analytics tools available today, but they are not connected to each other, therefore does not encourage the emergence of a common data network. So, in order to develop effective solutions necessary for education, IT companies, educational researchers and practitioners, policy makers should be strongly interested in cooperation,
- Data-driven decision-making skills are important for learning analytics user target groups to make objective decisions and learner-centered solutions.
- Learners need to understand the importance of learning analytics to their learning and experience its "empowering" effect.
- As data is collected from various sources and learning environments, researchers have an important task to develop such data analysis methods (algorithms) that would help to solve effectively learning-related problems.

- The application of learning analytics also raises questions related to data ethics and their confidentiality.

Actualizing the possibilities of artificial intelligence and learning analytics in European general education it is important to consider several aspects. One of them is related to those determined by technology changes in education towards lifelong learning. In this context, it is suggested to search answers to the following questions: how digitization could transform the education sector in the short, medium and long perspective; how fast, such as artificial intelligence, learning analytics, robotics, etc. i.e., advances change or may change teacher training and student learning? Another aspect emphasizes how education responds to change the needs of society and the labor market. Thus, the necessity of the 21st century is emphasized. discuss skills at different levels of education, emphasizing those that are difficult to 'automate' that drive innovation, such as creativity, critical thinking, communication and cooperation. In other words, the digitization of society and future labor markets changes in demand prompt consideration of the content and nature of education: what knowledge, abilities, attitudes and values do people need, especially in digitalized, artificial intelligence in an affected world? The aforementioned questions highlight further research, including inclusive ones application of artificial intelligence and learning analytics in education, direction.

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