Educational Data Mining and Learning Analytics in the 21st Century

Georgios Lampropoulos
https://orcid.org/0000-0002-5719-2125
International Hellenic University, Greece

INTRODUCTION

The digitalization of everyday life and the rapid technological advancements have helped the new generation of students be familiar with and accustomed to digital technologies from a young age. As a result, their educational needs and requirements as well as their viewpoints regarding what effective learning is have drastically changed. Moreover, while the need for basic education is becoming urgent, the current educational system struggles to satisfy the new educational requirements (Prensky, 2001) and students' need for more personalized learning experiences.

Simultaneously, an exponentially increasing amount of heterogeneous data which is characterized by its volume, variety, veracity, velocity and value is being generated (McAfee et al., 2012). This vast volume of data is called Big Data and it paves the way for technological advances. Data mining is a scientific field which has experienced drastic advancements due to the rise of Big Data and its being more broadly applied in a wide variety of domains.

Data mining, also known as Knowledge Discovery in Databases (KDD), utilizes a variety of algorithms, techniques and methods in order to generate knowledge by discovering novel and useful information, patterns, relationships or structures from large data collections (Fayyad et al., 1996; Witten & Frank, 2002). Therefore, it can be used as an invaluable tool that supports and enhances decision-making (Peña-Ayala, 2014). As a result, data mining along with the necessary analysis tools are utilized in various sectors. The educational domain is no exception to that as data mining can offer several benefits.

The main aim of this chapter is to offer an overview of educational data mining and learning analytics and their essential role in improving 21st century education while capitalizing on the emergence of data science. For that reason, it presents and analyzes the concepts of learning analytics and educational data mining, their evolution as well as their role in modern education and highlights the impact of machine learning on them. Moreover, the chapter goes over the recent literature and extracts invaluable information according to the results and outcomes of related studies. Furthermore, it discusses their use as useful tools in educational settings and as a means to offer intelligent personalized learning in order to meet the new and upcoming educational needs and requirements. In addition, it goes over the merits that they can yield, and it suggests ways to address some of the current open challenges and limitations. Finally, it presents the summary of the main findings, drawn conclusions and provides directions for future research.

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BACKGROUND

A lot of emphasis is put on the collection, processing and analysis of data so as to better comprehend and optimize the learning and teaching process and outcomes. Educational data mining and learning analytics are two fields which are becoming more popular due to this fact.

Educational data mining is a specialized form of data mining which focuses on educational environments. It aims at addressing educational issues by analyzing data and developing models that enhance the overall learning experience and outcomes and increase the institutional effectiveness (Baker and Yacef, 2009; Dutt et al., 2017). It is worth noting that due to its nature, it can be applied at all educational levels (Saa, 2016). According to the Educational Data Mining community, educational data mining can be defined as "an emerging discipline, concerned with developing methods for exploring the unique and increasingly large-scale data that come from educational settings and using those methods to better understand students, and the settings which they learn in" (Educational Data Mining Community, 2021). Based on this particular definition, it is apparent that educational data mining constitutes an interdisciplinary field. Therefore, it exploits machine learning, statistics, information retrieval, recommender systems and other innovative technologies and techniques (Romero & Ventura, 2010).

As a part of Technology-Enhanced Learning (TEL) research, learning analytics is another interdisciplinary scientific field which is gaining ground as it can enhance the existing education models (Ferguson, 2012; Siemens & Baker, 2012). It can be regarded as a powerful tool which explores how the large volume of data can be used to enhance the overall learning quality and to address a variety of educational challenges and issues (Bakharia et al., 2016; Pardo et al., 2019). Particularly, learning analytics involves the collection, analysis and visualization of data with a view to better comprehending and improving both learning experience and environment (Ferguson, 2012; Lang et al., 2017; Liñán & Pérez, 2015; Romero & Ventura, 2020; Siemens, 2013). The analysis and visualization of data can provide invaluable feedback for both students and teachers (Clow, 2013) and assist in fulfilling the new educational needs as well as positively affecting students' learning and progression (Slade & Prinsloo, 2013). Therefore, it can be regarded as an essential educational tool which can be further improved as the amount of data increases and machine learning algorithms and models become more advanced.

Even though these two fields seem similar at first sight, there are some distinct differences between them. Particularly, educational data mining follows a bottom-up approach as it aims at finding new patterns in data and developing new models while learning analytics follows a top-down approach to assess the learning theories and the educational process by utilizing existing models (Baker and Yacef, 2009; Bienkowski et al., 2012). Moreover, there are various distinctions between educational data mining and learning analytics regarding their origins, reduction and holism approaches, knowledge discovery aims and methods, adaptation and personalization strategies as well as the overall techniques and methods used (Liñán & Pérez, 2015; Siemens, 2012). It can be said that educational data mining focuses more on the technical challenges while learning analytics on the educational ones (Ferguson, 2012). Despite their main focus points, their successful implementation in educational settings can bring about numerous innovative and positive changes and yield several merits to satisfy the new educational needs and students' requirements.

FOCUS OF THE ARTICLE

With the multitude of sensory data that contains various semantics, formats and structures, the general field of data science is rapidly evolving. Due to its nature, it affects several domains, such as healthcare (Raghupathi & Raghupathi, 2014), industry (Lampropoulos et al., 2018), transportation (Zhu et al., 2018) etc. Particular interest is noticed in the field of education. As the educational sector employs a data-driven approach, both learning analytics and educational data mining are being widely accepted and adopted since they constitute powerful analytical and statistical tools that offer invaluable predictive models and decision-making systems and rules and enable educational institutions to stay ahead of the global competition by reducing their costs, increasing their income and productivity and providing education of higher quality (Liñán & Pérez, 2015).

SOLUTIONS AND RECOMMENDATIONS

As educational data mining aims at detecting patterns within large collections of data originating from educational environments (Hann & Kamber, 2000), it is closely connected with the fields of machine learning and deep learning (Hernández-Blanco et al., 2019). Particularly, machine learning constitutes a sub-field of artificial intelligence which aims at creating models that imitate the way that humans perceive things and learn by using data and algorithms while deep learning is a specialized form of machine learning with a multitude of layers through which the data is transformed (Lampropoulos et al., 2020). Moreover, it is worth noting that as traditional data mining algorithms satisfy only specific objectives and functions in order for them to be applied in educational problems, customized preprocessing algorithms need to be enforced first (Dutt et al., 2017).

Educational data mining can assist in assessing, predicting and analyzing students' academic performance and outcomes (Asif et al., 2017; Baradwaj & Pal, 2012; Fernandes et al., 2019) and it can provide ways to profile and group students, assess and grade students in an unbiased manner, detect undesirable behaviors, create concept maps and student models as well as to generate recommendations and evaluations (Bakhshinategh et al., 2018; Hernández-Blanco et al., 2019; Romero & Ventura, 2010; Salloum et al., 2020). In addition, educational data mining can be applied to improve student-centered and specific domain models, to assist in exploring pedagogical approaches as well as in supporting the implementation and justification of scientific research into learning and teaching activities (Baker, 2010; Baker and Yacef, 2009). Moreover, it creates methods to better assess and evaluate students' performance and the educational material used, provides learning recommendations based on specific and personalized students' needs and behaviors and constitutes a means that provides advanced feedback for both students and teachers (Castro et al., 2007).

With the aim of improving the educational process, learning analytics is used to generate actionable intelligence and reveal hidden information and patterns from raw data that derive from educational environments (Campbell et al., 2007; Siemens, 2012). Moreover, they can increase our comprehension regarding the learning and teaching processes as well as the educational environment itself by providing invaluable insight into learners' performance, behavior, interaction and learning paths (Vahdat et al., 2015). Particularly, with a view to optimizing learning, learning analytics enables the collection, process, measurement, analysis, reporting and visualization of educational data (Romero et al., 2010).

Learning analytics puts emphasis on performance management, metrics and quantification and utilizes statistical and computational methods and tools to manage and analyze large data sets that derive from the increasing number of learning activities that take place within learning management systems and virtual learning environments (Clow, 2013). Techniques and applications are the main overlapping components of learning analytics with techniques referring to specific models and algorithms while applications to how the specific techniques are implemented to improve the educational process (Siemens, 2013). When used in a student-centered way, learning analytics can constitute a useful educational tool that assesses and evaluates teachers' and instructors' pedagogical intent within learning and teaching activities and provides invaluable insights regarding their impact on students (Lockyer et al., 2013). Moreover, learning analytics supports adaptive learning, quality assurance and quality improvement, boosts retention rates, improves the quality of teaching, enables students to take control of their own learning and is positively perceived by students (Sclater et al., 2016).

Both educational data mining and learning analytics can enhance the educational process by providing computer-supported learning, behavioral, predictive and visualization analytics and by improving collaborative learning and social networking analysis (Aldowah et al., 2019). Additionally, they need to take the educational context into consideration, to be integrated into current e-learning systems and to be designed in a flexible and simple way so that it would be easier for the educators to learn and use them (Romero & Ventura, 2010). Understanding better how people learn and utilizing these methods efficiently can lead to designing more effective and smarter learning environments that will boost both learning and teaching activities (Baker, 2014). Moreover, in both cases, the primary areas of analysis can be categorized into: (i) prediction, (ii) clustering, (iii) relationship mining, (iv) discovery with models and (v) data distillation for human judgment (Baker et al., 2009). Furthermore, their areas of application can be grouped into: (i) trend analysis, (ii) personalization and adaptation, (iii) user profiling, (iv) knowledge domain modeling and (v) users' knowledge, behavior and experience modeling (Bienkowski et al., 2012).

FUTURE RESEARCH DIRECTIONS

Since both educational data mining and learning analytics are new research fields there still remain several issues and open research questions that need to be explored and addressed. As the fields evolve, there is a need for both analytic approaches and outputs to be aligned with conceptual frames of reference as well as the necessary for each case educational contexts (Bakharia et al., 2016; Gašević et al., 2015).

Moreover, as they both have strong roots and are interrelated with several fields of data mining, statistics and analytics, it is difficult to detect and retrieve the crucial for the comprehension of the learning process information regarding pedagogy, cognition and metacognition (Ferguson, 2012; Vahdat et al., 2015). Consequently, it is vital to enforce effective pedagogical methods, approaches and strategies. As a result, there is a great need to build strong connections with the learning sciences, concentrate on learners' perspectives and needs and create methods that can be applied in a wide variety of data sets (Ferguson, 2012).

It is evident that teachers and instructors lack the theoretical and practical knowledge regarding the use of the necessary tools (Liñán & Pérez, 2015). Therefore, in order for learning analytics and educational data mining to further advance, it is crucial to develop more freely available tools as well as general purpose ones and to enhance the promotion, adoption and development of a data-driven culture within educational environments and institutions (Romero & Ventura, 2013, 2020).

Moreover, both educational data mining and learning analytics can be particularly useful in cases where traditional informal monitoring is not possible such as online learning, as they can provide crucial monitoring, knowledge and decision-making support (Romero & Ventura, 2007). As online learning and virtual learning environments are becoming more widely utilized, developing and using advanced analytical and monitoring tools that can assist the overall educational process is vital. This is particularly helpful when augmented reality (AR), virtual reality (VR) and immersive 360-degree videos are utilized in the educational process so as to achieve a better understanding of the impact and benefits they can yield as they constitute innovative solutions that can enhance the educational process in an interactive, engaging and student-centered manner (Lampropoulos et al., 2021). Additionally, the majority of recent studies concentrated on predicting, grouping, modeling and monitoring learning activities solely based on classification, clustering, association rules, statistics and visualization techniques (Aldowah et al., 2019). Hence, there is a profound need for more customized and powerful educational data classification and clustering algorithms and methods to be developed (Dutt et al., 2017).

The majority of systems being used and studied are developed to address specific use cases or courses and for that reason, they cannot be generalized (Mohamad & Tasir, 2013). Therefore, it is apparent that in order to provide generalized results, future research should emphasize the collaboration of different fields so as to create broader use cases that will be able to be applied in various contexts, courses and educational environments. Additionally, more effort should be put into the increased collaboration among researchers and practitioners so as to develop more student-centered and advanced tools and techniques, to assess data related issues and enhance analytics performance and interpretation (Siemens, 2012).

According to Leitner et al. (2019), in order for learning analytics and educational data mining to be fully realized in higher education institutions, the challenges that need to be successfully met can be categorized into: (i) purpose and gain, (ii) representation and actions, (iii) data, (iv) IT infrastructure, (v) development and operation, (vi) privacy and (vii) ethics. Moreover, based on the study conducted by Baker (2019), some of the main general challenges that need to be addressed refer to: (i) transferability, (ii) effectiveness, (iii) interpretability, (iv) applicability and (v) generalizability.

It is worthwhile to mention that the majority of issues and challenges faced by analytics within the educational domain are mainly focused on data related issues such as openness, accuracy, quality and sufficiency (Siemens, 2013). Furthermore, due to data ethical and privacy concerns as well as a lack of a standardized representation, it is difficult to make the data available for research purposes despite the fact that more and more data is being collected from learning environments (Siemens, 2013; Verbert et al., 2012). Consequently, a specific emphasis should be put on addressing the open research questions regarding ethical and privacy principles, issues, dilemmas and practices for both educational data mining (Ihantola et al., 2015; Siemens, 2012) and learning analytics (Pardo & Siemens, 2014; Slade & Prinsloo, 2013). Ethics and privacy should be greatly taken into consideration in all stages, that is from the data retrieval and collection to the analysis, interpretation and decision making (Greller & Drachsler, 2012).

CONCLUSION

Nowadays, with a view to improving the educational process and addressing students' needs and requirements, more emphasis is put on the collection, process, analysis and visualization of data. Furthermore, the exponentially increasing volume of data has brought about not only new challenges but also new opportunities for innovative applications and solutions. Educational data mining and learning analytics are two of the most rapidly growing scientific fields which aim at providing insights into educational matters based on the analysis of data.

As learning analytics and educational data mining mature and provide enhanced insights into learning and teaching processes, they will be more widely used by the educational community. Additionally, as more educational institutions develop and adopt a data-driven culture that utilizes tools which provide predictive, diagnostic and descriptive analytics, more personalized, advanced and smarter learning environments that are able to offer customized experiences and meet students' specific needs can be developed.

All in all, both educational data mining and learning analytics have the potential to significantly influence the current educational system and provide opportunities for new learner-centered tools, methodologies and techniques to be developed. Nonetheless, there still remain open research issues and challenges that need to be met in order for them to be fully implemented in educational settings. Future studies should focus on these issues while also showcasing the potentials and benefits that learning analytics and educational data mining can render to further enhance their adoption, implementation and advancement.

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KEY TERMS AND DEFINITIONS

Big Data: An exponentially increasing volume of heterogeneous data which is differentiated from traditional data based on its volume, variety, veracity, velocity, and value.

Data Mining: It is also known as Knowledge Discovery in Databases (KDD) and refers to the use of algorithms, techniques, and methods in order to generate knowledge by discovering novel and useful information, patterns, relationships or structures from large data collections.

Educational Data Mining: It is a specialized form of data mining which focuses on utilizing data that derives from educational environments and aims at addressing educational issues and enhancing the overall learning experience, performance, and outcomes.

Learning Analytics: It is an interdisciplinary scientific field which examines the way in which data can be used to improve the overall learning quality and to address a variety of educational challenges and issues.