Şahin, M., & Yurdugül, H. (2020). Educational data mining and learning analytics: past, present and future. *Bartın University Journal of Faculty of Education*, 9(1), 121-131.

Bartın University Journal of Faculty of Education, 9(1), 121-131

buefad.bartin.edu.tr

Educational Data Mining and Learning Analytics: Past, Present and Future

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Article Info

DOI: 10.14686/buefad.606077

Article History:
Received: 18.08.2019
Accepted: 10.12.2019
Published: 01.02.2020

Keywords:
Educational data mining,
Learning analytics,
Past, present and future of educational data mining and learning analytics.

Article Type:
Review article

Abstract

Educational data mining and learning analytics have recently emerged as two important fields aimed at rendering e-learning environments more effective. Aim of this study seeks first to reveal the differences between these two fields and then to discuss the future of these concepts by evaluating how they changed throughout history. Educational data mining refers to uncovering the patterns hidden in the big data whilst learning analytics is the use of these patterns to optimize e-learning environments. One of the purpos
,es of the study is to add to the literature on the future trends regarding these concepts. The studies on the future of learning analytics are categorized in five main headings: personalization of learning processes, learning design, learning experience design, dashboard design and the Industry 4.0 applications. In the very near future, it seems that studies will be performed on EDM and the Industry 4.0 one of its application areas, "(Internet of Things-IoT)" and EDM has the potential to substantially help researchers in discovering the patterns in the interaction data in the Learning Management Systems and in designing more effective learning environments.

Eğitsel Veri Madenciliği ve Öğrenme Analitikleri: Dünü, Bugünü ve Geleceği

Makale Bilgisi

DOI: 10.14686/buefad.606077

Makale Geçmişi:
Geliş: 18.08.2019
Kabul: 10.12.2019
Yayın: 01.02.2020

Anahtar Kelimeler:
Eğitsel veri madenciliği,
Öğrenme analitikleri,
Eğitsel veri madenciliği ve öğrenme analitiklerinin dünü, bugünü ve geleceği.

Makale Türü:
Derleme makalesi

Öz

Eğitsel veri madenciliği ve öğrenme analitikleri son zamanlarda e-öğrenme ortamlarının daha etkili hale getirilmesi amacıyla kullanılan iki önemli alan olarak karşımıza çıkmaktadır. Bu araştırmanın amacı, öncelikle her iki çalışma alanı arasındaki farklılıkları ortaya koymak ve diğer taraftan bu kavramlara ilişkin değişimleri tarihsel gelişimleri içerisinde değerlendirmektir. Eğitsel veri madenciliği büyük veri içerisindeki örüntülerin keşfedilmesini ifade etmekte iken, öğrenme analitikleri elde edilen bu örüntülerin e-öğrenme ortamlarının iyileştirilmesi için işe koşulmasıdır. Eğitsel veri madenciliği veri tabanında bilgi keşfi süreçleri ile ortaya koyulmaya başlamışken, öğrenme analitikleri ise özellikle 2011 yılında bu veri tabanlarından elde edilen örüntülerin işe koşulması olarak araştırmalardaki yerini almıştır. Araştırmanın amaçlarından bir tanesi ise bu kavramların gelecekteki yönelimlerine yönelik alan yazına katkı sağlamaktır. Öğrenme analitiklerinin geleceğine yönelik çalışmalar beş temel başlık altında ele alınmıştır. Bu çalışma başlıkları; öğrenme süreçlerinin kişiselleştirilmesi, öğrenme tasarımı, öğrenme yaşantıları tasarımı, öğrenme panelleri tasarımı ve Endüstri 4.0 uygulamaları şeklindedir. Çok yakın bir gelecekte EVM ve Endüstri 4.0 uygulama alanlarından birisi olan "Nesnelerin İnterneti (Internet of Things-IoT)" alanlarında çalışmaların yürütüleceği ve özellikle Öğrenim Yönetim Sistemlerinde (ÖYS) yer alan etkileşim verilerindeki örüntülerin keşfedilmesi ve daha etkili öğrenme ortamlarının tasarlanmasında araştırmacılara önemli bir güç katacağı düşünülmektedir.

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Introduction

Educational data mining (EDM) and learning analytics (LA) proved to be two notable themes in the field of education/teaching technologies in the last 10 years. Before elaborating on these two themes, it is worth identifying the difference between the concepts of analysis and analytics. If data are considered as the observation values of the characteristics of concepts, it is possible to reach out information by processing these data. At the heart of these processes, there is an attempt of uncovering hidden patterns embedded in raw data, and this whole process or procedure is referred to as analysis. Further, the attempt of uncovering these patterns contributes to not only a) the existing theoretical knowledge in the relevant field, but also b) the decision-making processes in the related area. The use of the patterns obtained from analysis in the decision-making processes is particularly discussed in relation to the concept of analytics. Briefly stated, analysis refers to identifying the patterns in data sets whereas analytics refers to the use of these patterns. When considered as a process, pattern discovery process is mostly studied in the framework of data mining; the use of the information obtained from this process is called analytics. Both data mining and analytics incorporate distinctions specific to the fields. In this regard, data mining based on educational data is named as "educational data mining" and the use of the patterns based on educational/instructional data is called learning analytics. However, educational data mining and learning analytics feature similar steps as a process, which creates a conceptual confusion. On the other hand, these fields have historically evolved into two diverse concepts. These being said, this study seeks first to reveal the differences between these two fields and then to discuss the future of these concepts by evaluating how they changed throughout history.

Educational Data Mining

The standardization of the ASCII codes by ANSI in 1963 has been a particularly important milestone for many areas in regard to the development of information technologies. Since, when one thought of data, the first thing that came to mind had been numbers until the year 1963. Yet, the introduction of the ASCII characters made it possible to store text-based information in digital environments. Then, visual and auditory data began to be recorded on the disk surfaces. Given that a 'file' as a computer concept is composed of data and command sets stored on the disk surfaces, it becomes clearer what the diversity of data types refers to. The data unit of the floppy disks used in the past was kilobytes, while that of the hard disk drives developed later on was megabytes; with the help of rapidly developing technologies, this unit evolved into gigabyte-terabyte with disk directories and today petabytes are used to refer to data volumes thanks to cloud technologies. This can be seen as an indicator of the development of data in about 50-60 years.

As scales of the digital data (volume) increased, the process of uncovering the patterns hidden in the data became more systematic and this process is referred to as Knowledge Discovery in DataBase (KDD). This concept, which outlines data mining, has been used primarily in enterprises (where it is vital to make accurate and fast decisions). In this sense, data mining also refers to the process of revealing previously unknown useful information, trends and/or patterns from the bulky data stored in databases (Thuraisingham, 2014; Kantardzic, 2011; Yin, Kaku, Tang, and Zhu, 2011). This process consists of the following steps: a) defining problems or constructing hypotheses, b) targeting the data in the database, c) pre-processing the data (de-noising, conversion, scaling, dimension reduction, feature extraction, etc.), d) the use of data mining algorithms and, e) pattern/correlation recognition.. This process is shown in Figure 1.

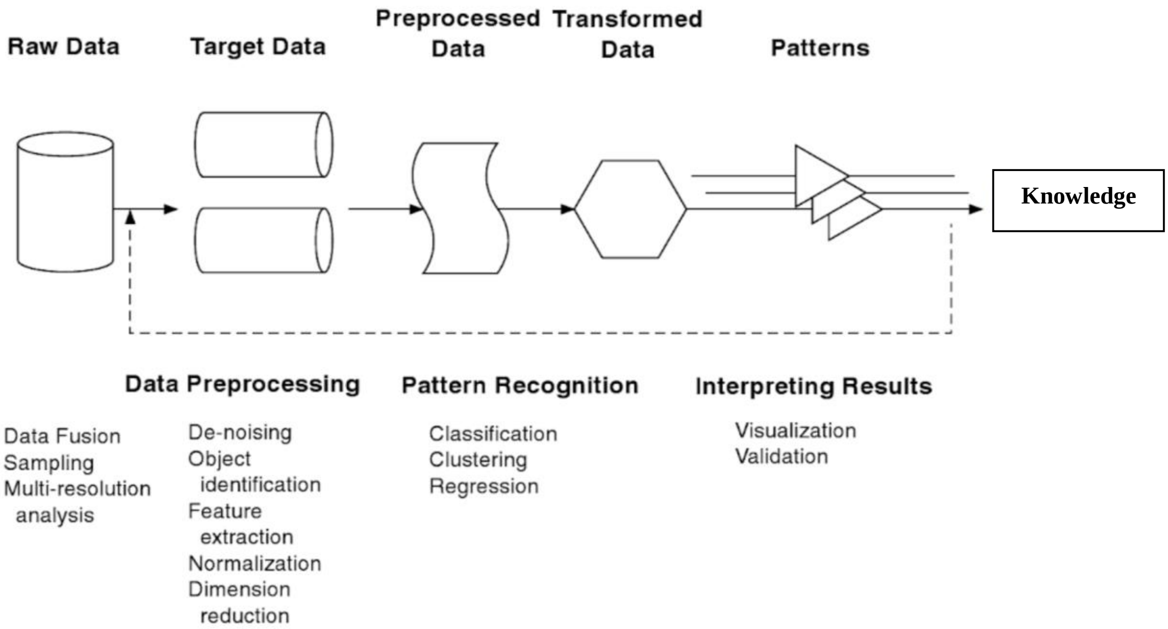

Figure 1. Schematic Process of Data Mining (Keyes, 2006)

Figure 1 presents the schematic process diagram for data mining. This process involves the stages of a) selecting the data hidden in the databases, b) pre-processing the selected data (processes related to noisy data and missing observations, data conversions, feature extraction and feature inclusion, dimension reduction, etc.), c) pattern recognition (classification, clustering, relationship mining, sequential analysis etc. algorithms) and d) the presentation of the findings and information obtained.

The information dimension, which is the stage after pattern recognition in the data set, is related to the use of the information obtained in the decision-making process and since the use of information implies intelligence, this process and its follow-up process is called business intelligence (Keyes, 2006).

In educational environments, learners leave a lot of unstructured traces (log data) behind in e-learning environments. Educational data mining allows for uncovering the meaningful and implicit patterns from these unstructured data of the learners. Educational data mining refers to the development of various methods to reveal the significant and implicit patterns from the data that are present in educational environments in structured and/or unstructured way and the use of the methods developed accordingly (Baker and Siemens, 2014). Several methods such as estimation, structure discovery, relationship mining can be employed in the use of these implicit patterns. The method/s to be employed may vary according to the purpose of the study. Prediction models include classification and regression; structure discovery includes clustering and factor analysis while relationship mining incorporates association rule and sequential pattern mining (Baker and Inventado, 2014).

Past and Present of EDM

Many resources on the history of data mining have identified the beginning of data mining with the history of the algorithms used in data mining. For example, there are some studies that point to the Bayes theory in the 1700s or regression analysis in the 1800s (Berry and Linoff, 2004). These studies also highlight neural networks, clustering, genetic algorithms (the 1950s), decision trees (the 1960s), and support-vector machines (the 1990s) (Wu et al. 2008).

The first application of data mining in education is the study by Sanjeev and Zytkow (1995) that seeks to make institutional decisions in a university database. Further, there are workshops and conferences in the literature on the field of EDM. The first conference on EDM was the "International Conference on Artificial Intelligence in Education" in 1982 and the first workshop was the "Workshop on Applying Machine Learning to ITS

Design/Construction” in Canada (Romero and Ventura, 2013). Figure 2 presents the historical development of the field of EDM.

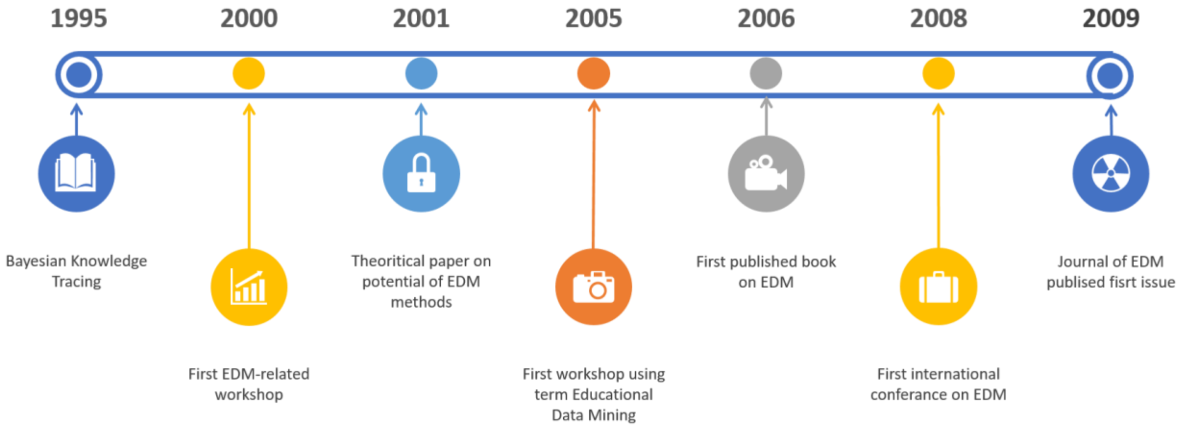

Figure 2. Historical Development of Educational Data Mining (Baker and Inventado, 2014)

As seen in Figure 2, 1995 and the 2000s witnessed the development of the first algorithms and the organization of the first workshops. Hence, publications were made based on the emerging knowledge and the EDM magazine was commenced. The year 2011 featured the first concrete examples of the applications of EDM algorithms in online learning environments with the use of learning analytics.

The studies on EDM are as follows in chronological order:

- The years between 1995-2005 focused on relationship mining,
- Prediction methods were popular from 2005 to 2009,
- Various methods such as the Item Response Theory, the Bayesian Network and Markov Chain have been used in the framework of psychometric analysis and learner modeling since 2009 (Baker and Yacef, 2009).

Today, there are four basic domains when it comes to the key application areas of EDM. These domains are identified as follows by Baker (2010):

- Student Model: Modelling of students according to different personal characteristics including prior knowledge, attitude, motivation and meta-cognition strategies.
- Domain Model: Discovering or improving models of the knowledge structure of the domain.
- Pedagogical Support: Improving and testing the applications that may provide pedagogical support such as discovering which pedagogical support is most effective for which student.
- Investigating the key factors that affect learning in more depth in order to design better learning environments and providing empirical evidences.

Worth mentioning here is the relationship between educational data mining and learning analytics that include similar aspects but are aimed at shaping instructional design and processes, particularly in 2011-2012. Although the essence and boundaries of both concepts (educational data mining and learning analytics) were vague in these years, these concepts are today well-defined. Siemens and Baker’s (2012) study titled “learning analytics and educational data mining: towards communication and collaboration” serves as a manifesto and calls for resolving this confusion, determining the boundaries of these fields and collaboration.

Future of EDM

EDM enables researchers to discover patterns by using various data including learner interaction data, self-report data and data warehouses. In addition to these data obtained in the virtual web, many data from the physical web obtained through sensors are now included in the big data. These sensor technologies are featured as an application of the Industry 4.0. The use of these sensor technologies in education is a recent development. With the improvement of such applications, sensor technologies can transfer and store a lot of data about educational environments. And, EDM will allow for the identification of patterns from these data. In the very near future it seems that studies will be performed on EDM and the Industry 4.0 and one of its application areas, "(Internet of Things-IoT)."

EDM has the potential to substantially help researchers in discovering the patterns in the interaction data in the Learning Management Systems (LMS) and in designing more effective learning environments. It is further reported that EDM would provide opportunities for researchers and designers to develop personalized learning environments and suggestion systems (Huebner, 2013). Besides, it can be used in developing decision support systems to minimize instructional intervention (Bienkowski, Feng, and Means, 2012).

Today, EDM more focuses on "student model", which is a key component of learning systems, compared to learning analytics. Naturally, the most important study area of EDM is Intelligent Tutoring Systems (ITS) where there is no human tutor. On the other hand, LA usually plays a critical role in the design of LMS. Hence, studies on the integration of LMS and ITS to combine the forces of EDM and LA have increased in the recent times (Aleven et al. 2015; Aleven et al. 2016). Indeed, Aleven et al. (2015) titled their study "The Beginning of a Beautiful Friendship? Intelligent Tutoring Systems and MOOCs."

Promising subjects for the future of EDM include updating, optimizing and improving algorithms based on machine learning and expert systems in artificial intelligence applications in education.

Learning Analytics

The study (two sigma problem) by Bloom (1984) reported that one to one tutor support increases learners' learning outcomes by two standard deviations. Thus, with developing technology, various e-learning environments have been presented to learners to support and improve learners' learning processes. These environments are the environments in favor of autonomous learners, that is, the learners who take responsibility for their own learning and organize their own learning experiences. However, these e-learning environments fail to support learner autonomy (Simic, Gasevic, and Devedzic, 2004). Educational data mining and learning analytics offer some important opportunities to overcome the drawbacks of e-learning environments (Shabani, Zahra, and Eshaghian, 2014). This section presents information on learning analytics as the previous one is on educational data mining. Learning analytics is the measurement, collection, analysis and reporting of data about learning environments for the purposes of understanding and optimizing learners and the environments in which it occurs (Siemens and Gasevic, 2012). A key concern of learning analytics is the gathering and analyzation of data as well as the setting of appropriate interventions to improve the learners learning experience (Greller, Ebner, and Schön, 2014). Based on these definitions, it can be stated that educational data mining refers to discovering the implicit patterns hidden in the data on education environments whilst learning analytics refer to the use of these implicit patterns uncovered to improve learning environments. Learning analytics are involved in an iterative and a formative process. Figure 3 shows the processes related to learning analytics.

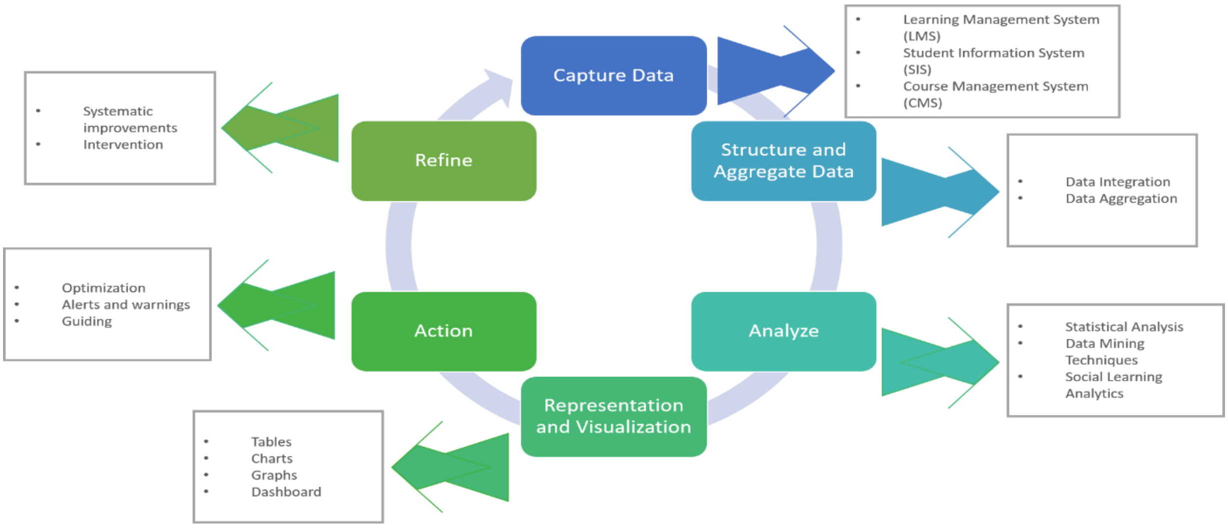

Figure 3. Learning Analytics Process (Lal, 2014)

As seen in Figure 3, learning analytics process has a cyclical structure, which starts with capturing data and ends with refining. The outputs of one study are the inputs of the next study in learning analytics studies. As for the data of learning analytics, the following sources can be used: Learning Management Systems (LMS), Student Information Systems (SIS), E-Learning Environments and recently developed Intelligent Tutoring Systems (ILMS). The next step after capturing data is structuring the data, that is, obtaining quality data, and making the data ready for analysis. Educational data mining processes and techniques are employed in this step. In the analysis step, different methods such as statistical analyses, data mining techniques, social learning analytics, etc. can be used. Following the recognition of implicit structures and patterns in the analysis step, information can be presented to learners, tutors, researchers and managers, namely stakeholders, by using tables, charts, graphics, word clouds and learning dashboards. The process of designing the system is followed by the action step where the developed environments are presented to stakeholders. The last step is refining, which involves systematic improvements. After this step, the outputs and data obtained from this study are used as the input and data of the next study, and the learning analytics process continues in an iterative and a formative way.

Some reference models have been introduced to ensure a better understanding of learning analytics and these models seek to answer some questions. One of those models is the reference model put forward by Chatti, Dyckhoff, Schroeder, and Thüs (2012), which is shown in Figure 4.

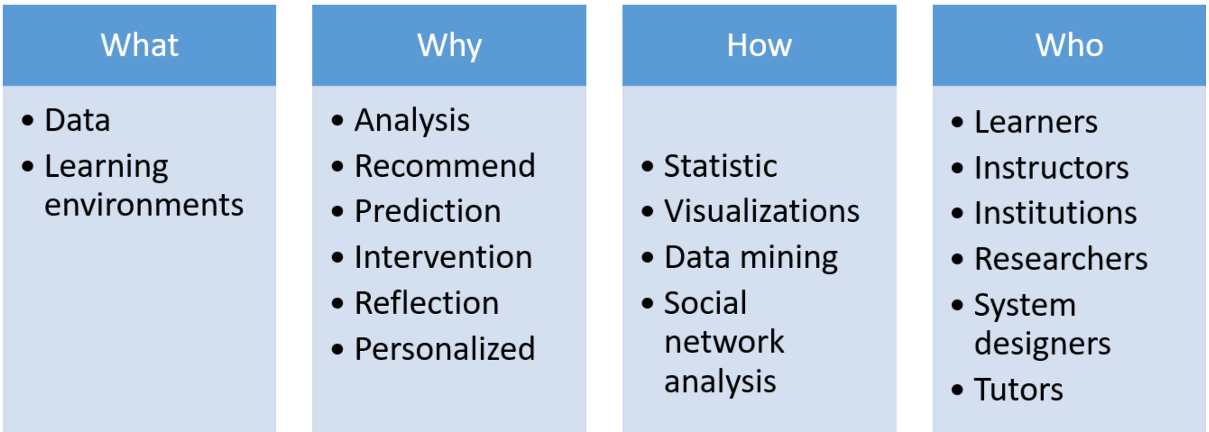

Figure 4. Learning Analytics Reference Model (Chatti, Dyckhoff, Schroeder, and Thüs, 2012)

Figure 4 shows that learning analytics basically seek to answer what, why, whom and how questions for the optimization of learning environments. Learning analytics utilize learning management systems, content management systems, student information systems, etc. as data sources. Based on these data, a lot of information and resources are offered to learners, tutors, managers, institutions, researchers and designers. Learning analytics enable a) learners to have adaptive feedbacks, recommendations and improve learning performance, b) educators to understand their students' learning processes and understand social, cognitive and behavioral aspects, c) researchers to evaluate learning effectiveness, d) administrators to assess the effectiveness of their institutional resources (Romero and Ventura, 2013). Based on purpose, these data can be used for analysis, prediction, intervention, mentoring, evaluation, adaptation, personalization, reflection, etc. In that regard, learning analytics can be utilized through different techniques such as statistics, data mining, social network analysis, visualization. It is worth noting that learning analytics use visualization as a technique. Some studies consider learning analytics merely as learning dashboards. Yet, learning analytics are a much broader concept. Learning dashboard is the application of the analytics used to interpret teacher and student findings, including the visual presentation of the data obtained through data mining (Pardo and Dawson, 2016). Learning dashboards are a visual element used for the presentation of learning analytics.

Past and Present of Learning Analytics

The studies on learning analytics can be grouped in three periods: a) the studies performed before 2011, b) the studies performed between 2011-2014 (the 2011 Learning Analytics Conference) and c) the studies performed after 2014 (Journal of Learning Analytics) (Peña-Ayala, Cárdenas-Robledo, and Sossa, 2017). Yet, learning analytics were presented in the time-to-adoption horizon of 4-5 years in the 2011 Horizon Report prepared by the New Media Consortium and in the 2011 Learning Analytics Conference, which attracted the attention of researchers. Further, in 2019, analytics technologies were considered in the horizon of one year or less. Learning analytics were first introduced in 2011 and is now a young field of research with increasing popularity. The following fields contribute to the development of this young field: a) citation analysis, b) social network analysis, c) user modelling, d) education/ cognitive modelling, e) tutors, f) knowledge discovery in databases, g) adaptive hypermedia and h) e-learning (Siemens, 2013).

In the initial studies, learning analytics were merely considered as a type of learning dashboards (Şahin, 2018). Yet, learning dashboards are one of the means to present the uncovered patterns. Learning analytics are far from being merely learning dashboards; it is a much broader concept. Learning analytics include interventions to the system or the individual. The interventions to the system are made through adaptive engines whilst those to the individual are made with intervention engines. There are a number of studies on adaptive engines, but the studies on intervention engines are limited. The study by Mckay et al. (2012) titled E^2Coach (Electronic and Expert Coach) may be considered as an example for these studies. Another study on this field is Arnold and Pistilli's (2012) study titled Course Signal. These two studies can be named as the first and pioneering studies where learning analytics are used in the context of intervention to learning environments and learning process. Other studies on intervention engines in the literature also include intelligent systems; indeed, Tlili et al. (2018) developed iMoodle and Şahin (2018) introduced the Intelligent Intervention System.

Learning dashboards served as a tool to provide only feedback interventions in the past. These interventions were structured based on the design elements of a visual message. However, today, it is possible to design not only feedbacks but also feed-forwards through learning dashboards. In this sense, the concept of intervention cannot be reduced to feedbacks. Since the concept of intervention incorporates both feedbacks and feed-forwards. It can be thus said that every feedback is a kind of intervention, but not every intervention is a feedback. Learning dashboards can be structured in different ways according to educational, supportive and motivational intervention types. Efforts are already underway to better design learning dashboards.

Future of Learning Analytics

In this study, the studies on the future of learning analytics are categorized in five main headings: a) personalization of learning processes, b) learning design, c) learning experience design, d) dashboard design and e) the Industry 4.0 applications. This section elaborates on these concepts.

It is important for the future of learning analytics that learners personalize their learning processes (Siemens, 2013). In using learning analytics to personalize learning environments and improve learning experiences, learning analytics were not discussed in relation to their potential in daily teaching activities (Bakharia et al., 2016). One of the things that come to mind when one thinks of the personalization of learning processes is learning design. Learning design is a methodology used to design learning activities and interventions with the effective use of concepts and technologies (Conole, 2012), which focuses on the learner context and constructivist approach in learning activities (Mor and Craft, 2012). Since learning design deals with the ways to optimize learning environments or to design different interventions for learning environments. The concept of learning design was first articulated in the Larnaca Declaration in 2012. Afterwards, many researchers, particularly those in the Open University in London, studied this concept. There is a notable pedagogical gap between learning analytics and learning design in the studies on learning analytics (Bakharia et al., 2016). Many data are already stored in learning environments and can be processed by various methods. Yet, learning design helps researchers in determining which metrics in these data have an important role in media and instructional design. Therefore, it seems that the gap between learning analytics and pedagogical information can be addressed by combining learning design and learning analytics. To offer a solution for this problem and to represent it, some frameworks have been put forward by researchers. The advantage of developing a common framework should be seen in establishing understanding, validity, reliability and direct support by clear guidance of the types of analytics and tools essential for particular learning contexts (Mangaroska and Giannakos, 2018). A review of the literature reveals the Learning Analytics Design put forth by Ifenthaler (2017), the framework for temporal analytics, tool-specific analytics, cohort dynamics, comparative analytics and contingency developed by Bakharia et al. (2016) as well as the Analytics Layers for Learning Design (AL4LD) introduced by Hernández-Leo et al. (2019).

One of the advantages of learning analytics and learning design is that it is possible to determine which learning designs lead to higher achievement and better student engagement (Nguyen, Rienties, Toetenel, Ferguson, and Whitelock, 2017). More research on learning design and learning experiences can be performed to further improve learning analytics. Learning experiences design includes support and guidance to learners in their learning experiences rather than instructors and designers. Learning design is a methodology for enabling teachers and designers to make more informed decisions in how they go about designing learning activities and interventions, which makes effective use of appropriate resources and technologies (Conole, 2012). In this regard, it is expected that learning design guides teachers and designers about the types of interventions, content and learning activities that will be present in the system. Moreover, it can offer insights into which designs are favored more by learners. The design of learning experiences includes the processes related to learners rather than instructors and designers. Learners are provided with support and guidance throughout their learning experiences.

Moore (1989) reported three types of interaction in learning environments: learner-content, learner-learner and learner-instructor interactions. Yet, with technological developments, these types have improved and new types of interaction have been introduced. Learners in online learning environments can also interact with their assessment tasks (Özgür and Yurdugül, 2016). Today, the interaction with learning dashboards, which are one of the applications of learning analytics, is considered as a type of interaction too (Khan ve Pardo, 2016; Rei, Figueira ve Oliveira, 2017). As learners can be provided with information, such as daily individual performance, comparison of individual performance with group performance, and estimated success, through these learning dashboards. The knowledge of which performance indicator/s reviewed by the learner for a longer time and of what kind of interaction pattern the learner is involved in after their review, offers some important insights for researchers and designers. This allows for the improvement of designs based on the revealed patterns.

One of the promising fields for the future of learning analytics is the Industry 4.0 applications. Particularly Internet of Things (IoT) and Internet of Educational Things (IoET), which is an extension of IoT in learning environments, are expected to play a critical role in the studies on learning analytics. Since sensor technologies are today widely used in almost every area and the data obtained from these sensors are gathered in data warehouses to yield significant patterns. These patterns are shared with the stakeholders. The purpose of learning analytics is to optimize learning environments; so, in this way, not only the interaction data (log data) in learning environments but also the data obtained from sensors in the future can be utilized to optimize these environments.

Discussion and Conclusion

This study is concerned with the concepts of educational data mining and learning analytics, which has considerably expanded as a study field especially after 2011 and were included in several Horizon Reports. Accordingly, it first describes the concepts of educational data mining and learning analytics and offers a historical overview of the concepts. It is notable that there has been an ongoing conceptual confusion regarding educational data mining and learning analytics. Yet, these concepts are based on two different areas. EDM is rooted in educational software and student modelling; in contrast, LA origins are related to the semantic web, "intelligent curriculum", outcome prediction and systemic interventions (Romero and Ventura, 2013). This study also aims to reveal the differences between these concepts. It presents the historical development of educational data mining, its stages, algorithms or methods, as well as its past, present and future. It further includes the processes of learning analytics and the questions it seeks to answer. The previous and current studies on learning analytics as well as subjects that may be promising for further studies are covered in this study to guide and lead the way for researchers. This study will potentially help researchers in studying educational data mining and learning analytics by enabling them a) to understand these concepts and their differences, b) to have an understanding of the processes related to them, c) to gain insight into the previous studies and d) to develop a perspective towards future studies in the field.

Although it is reported that EDM and LA follow a common goal, which is to optimize learning and to increase performance, they are occasionally mistaken for each other. They consist of components similar both in terms of process and origins. Thus, these concepts were intertwined until 2011; yet today, they are differentiated from each other by clear boundaries.

Their similarities and differences should be discussed in two levels: a) process and b) application. To clarify the link between these two concepts in terms of process, it is useful to mention an analogy based on the concepts of analysis and analytics: "Is it analysis or analytics?" Whilst analysis seeks to reveal the links and patterns hidden in data, analytics is about the presentation and communication of the information obtained from the patterns for effective decision-making. In this analogy, the concept of analysis refers to EDM whereas the concept of analytics refers to LA.

As for application, EDM mostly deals with automated systems based on the student model (where human intervention is minimal) while LA is about system designs where an instructor is present. To elaborate further on this point, the above-mentioned definitions involve an effective decision-making based on the patterns in the data and it is critical who makes the decision. If it is the machine who will make the decision based on the information obtained from the patterns (automated processes), this learning practice can be considered as an application of EDM. On the contrary, if it is a human, e.g. the instructor or learner, this can be considered as an application of LA.

Thus, the Intelligent Tutoring Systems are based on EDM and particularly on the user model. However, the pre-configured applications such as Learning Management Systems focus on LA more. This distinction can be also made with the presence or absence of a human tutor. A learner needs two different interventions/support in a learning process in the context of out-of-school teaching technologies. These are respectively supports required by the learner in learning and problem-solving steps. The supports in learning process are rather educational, supportive and motivational interventions. Those in problem-solving steps benefit from tutoring systems. These systems focus more on the intensive user model, the dynamic Bayesian networks, the Hidden Markov models and an extension of these models, namely the "Bayesian Knowledge Tracing" models; and, these approaches have been substantially studied in relation to EDM.

Today, there are ongoing efforts to reunite these two fields, which were separated from each other by clear lines in 2011. The greatest motivation behind these efforts is to make the new generation Learning Management Systems (LMS) intelligent and to combine MOOCs with Intelligent Tutoring Systems in a single system, since it is believed that video analytics, text analytics and learning dashboards in MOOCs fail to support the learner's learning experience. Barenes et al. (2016) emphasized that Massive Open Online Courses (MOOC) systems like EdX, Coursera, Canvas and UdaCity are limitedly supported by learning analytics and that it is necessary to improve these systems and combine them with ITSs to support the learner in problem-solving steps, and further to integrate the data of both systems. This emphasis is also to co-use LA and EDM in application.

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