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Educational data mining and learning analytics for 21st century higher education: A review and synthesis

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ABSTRACT

The potential influence of data mining analytics on the students' learning processes and outcomes has been realized in higher education. Hence, a comprehensive review of educational data mining (EDM) and learning analytics (LA) in higher education was conducted. This review covered the most relevant studies related to four main dimensions: computer-supported learning analytics (CSLA), computer-supported predictive analytics (CSPA), computer-supported behavioral analytics (CSBA), and computer-supported visualization analytics (CSVA) from 2000 till 2017. The relevant EDM and LA techniques were identified and compared across these dimensions. Based on the results of 402 studies, it was found that specific EDM and LA techniques could offer the best means of solving certain learning problems. Applying EDM and LA in higher education can be useful in developing a student-focused strategy and providing the required tools that institutions will be able to use for the purposes of continuous improvement.

1. Introduction

Data mining techniques are increasingly gaining significance in the education sector. As in many other sectors, higher education is discovering the potential impact of these techniques on the learning process and outcomes in order to move towards a university of the new era. Certainly, data mining techniques can provide educational policy makers with data-based models essential for supporting their goals to enhance the efficiency and quality of teaching and learning. In this sense, the use of different data mining techniques can be viewed as potential groundwork for a systemic change and it can have a significant positive impact if it is seen and serve as an instrument that can help higher education institutions find out solutions for their most specific issues (Van Barneveld et al., 2012). Thus, outcomes from data mining applications can provide invaluable support for the decision-making process (Peña-Ayala, 2014). Educational data mining (EDM) and learning analytics (LA) are two specific areas that are used to represent the use and the application of data mining in higher education and other educational settings. They establish an ecosystem that can consecutively collect, process, report and work on digital data continuously in order to improve the educational process. The use of EDM and LA in the educational context has the potential to shape the existing models of teaching and learning by providing new solutions to the interaction problem (Brown et al., 2015). A learning management system (LMS): a virtual learning environment that enables the management and delivery of learning resources to students: provides a limited understanding of learning-related issues. As such, EDM and LA are used to offer more personalized, adaptive, and interactive educational environments to enhance learning outcomes, teaching and learning effectiveness, and optimizing institutional proficiency, as well as mapping both instructor and student performance (Papamitsiou and Economides, 2014). The current movements to generalize the use of EDM and LA in higher education

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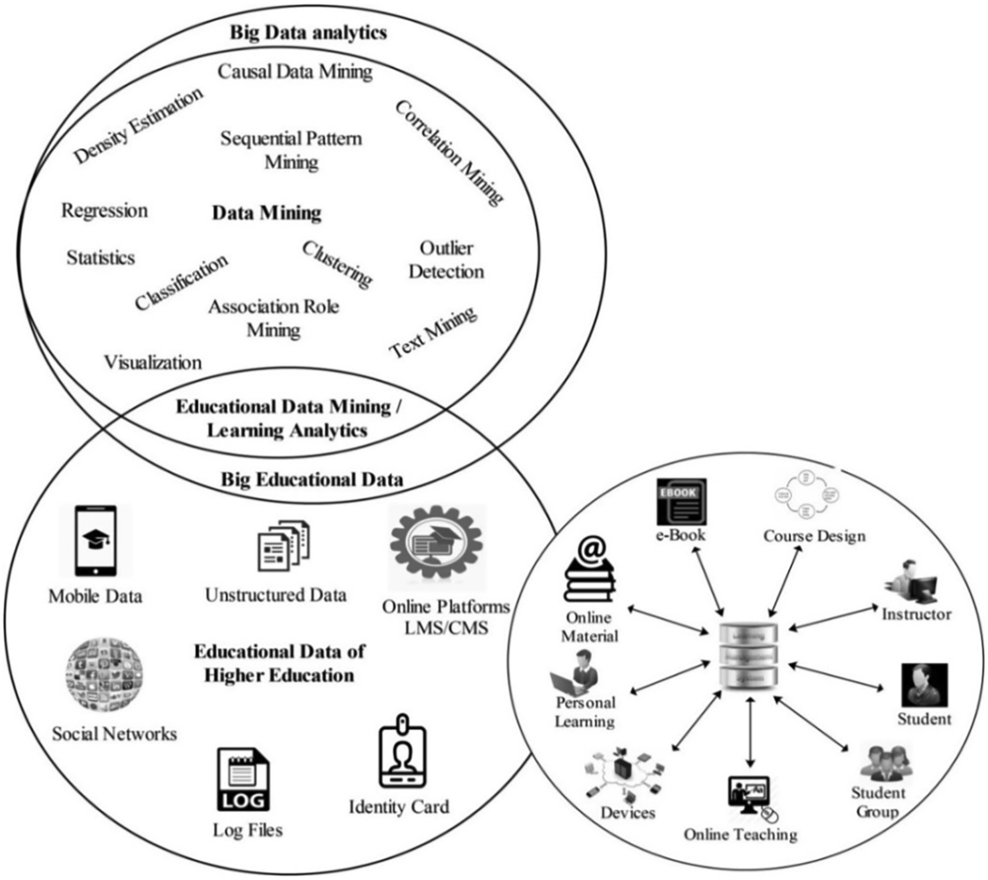


Fig. 1. An illustration of data mining (EDM and LA) use in higher education.

have resulted in many studies on the effectiveness of such usage in an online context. This led universities to collect large volumes of data relating to their students and the learning process stored in learning/content management systems (LMS/CMS) (Tair and El-Halees, 2012).

The current literature regarding the use of data mining in the higher education sector is mainly concentrated on the use of techniques such as classification, clustering, association rules, statistics and visualization to predict, group, model, and monitor various learning activities. EDM/LA researchers provided further dimensions concerned with academic activities, including computer-supported collaborative learning for the purpose of mining collaborative patterns in educational discussions (D'Mello et al., 2010; Perera et al., 2009), supporting instructors in collaborative student modeling (Gaudioso et al., 2009), evaluation of university learning material and curriculum improvements (Campagni et al., 2014; Jiang et al., 2016), identify factors associated with students' success, failure, and dropout intention (Cambruzzi et al., 2015; Lykourentzou et al., 2009; Márquez-Vera et al., 2016), institutional planning and strategies (Caputi and Garrido, 2015; Mankad, 2016), as well as understanding the instructors' support and administrative decision making.

However, the application of data mining in higher education is still in its infancy stage and needs more attention. Fig. 1 provides an illustration of data mining (EDM and LA) use in the educational field mainly to enhance students' understanding of the learning process by identifying, extracting and evaluating variables related to the students' characteristics or behaviors (Baradwaj and Pal, 2012). The processes of using EDM and LA to improve the quality of decision making have become a challenge that institutions of higher education face today (Sacin et al., 2009). This is where data mining methods come in handy to convert all information (e.g., learning objectives, learning activities, learning preferences, participation, competences, performance, and achievements) resulting from students' participation in various learning activities so that educational policy makers can use to make informed decisions (Ji et al., 2016).

Previous reviews on EDM and LA (e.g., Romero and Ventura, 2010; Sacin et al., 2009; Schrire, 2004; Van Barneveld et al., 2012) have provided substantial insight on the theoretical basis of this rapidly growing field (see Section 2). However, these reviews did not consider the association between different EDM and LA techniques for solving specific educational problems and did not produce a clear classification of the dimensions in which these techniques can be successfully used and applied in the higher education sector. In other words, there is a notable lack of evidence concerning the potential association between certain educational problems and techniques of EDM and LA for solving these problems. Furthermore, most previous reviews in this area have covered research works conducted in the field until 2013 and within a specified period. Therefore, the aim of this paper is to provide a more current review on the applications of EDM and LA in a university context with the objective of addressing the relationship between the purpose of its utilization and the techniques that were applied. It is hoped that this review will function as a guide for future studies on the use of EDM and LA techniques for solving specific learning and teaching problems.

2. Previous reviews on EDM and LA

In this section, a number of comprehensive review studies that have been carried out in the past are presented to address the potential of EDM and LA at different educational levels and settings. As EDM and LA are grounded on data mining, most of previous reviews on data mining techniques and their applications were of a technical nature and carried out during the last decades. The first and most popular review was conducted by Cristobal Romero and Ventura (2007) who described data mining techniques (from 1995 to 2005) in different educational systems. The authors discussed how certain data mining techniques, such as statistics and visualization, clustering, classification and outlier detection, association rule mining and pattern mining, and text mining, have been used with web-based courses, LMS, and intelligent web-based systems. The authors concluded that more specialized research is needed in EDM in order to become a mature area. Later, Romero and Ventura (2010) extended their previous review on EDM by covering more aspects related to the groups of users, types of educational environments and the data provided. They also listed the most common tasks in the educational environment that have been resolved through data-mining techniques based on eleven educational categories.

Baker and Yacef grouped papers according to EDM methods and applications. They suggested four applications of EDM: student models, domain models, pedagogical support, and scientific research. In 2009, Pena, Domínguez, and Medel published a review paper on computer-based educational systems, data mining, and EDM with respect to computer-assisted instruction, intelligent tutoring systems, LMS, and web-based educational systems. In 2013, another survey was published by Huebner (2013) with regards to student retention and attrition, personal recommender systems, and course-related data. However, the paper did not present any description of the data mining methods in an educational context. In the same year, Romero and Ventura (2013) offered a comprehensive review of the current state of data mining in education (citing 67 previous studies) on the use of EDM for knowledge discovery. Their review was limited to the role of EDM in facilitating the exploration of learning models for specific purposes. Papamitsiou and Economides (2014) surveyed previous works ON EDM and LA (from 2008 to 2013) using 40 studies by looking at the issues related to student behavior modeling, prediction of performance, increase of students' and teachers' reflections, improvement of feedback and assessment services. Peña-Ayala (2014) reviewed EDM works (from 2010 to 2013) by organizing them into six clusters related to student modeling, student behavior modeling, student performance modeling and assessment, student support, feedback, and knowledge-sequencing-teaching support.

Based on these reviews, there seems to be a need for expanding these reviews to show how specific EDM and LA techniques can be used to solve learning problems. Furthermore, most of these reviews covered works conducted in the field until 2014. Therefore, the aim of this paper is to provide an up to date review on the current trends of EDM/LA techniques in a university context.

3. Method

Two questions guided this research: "How can we use EDM and LA to solve practical challenges in education?" and "What data mining techniques are best suited to these problems?" To answer these questions, a comprehensive review on EDM and LA utilization was conducted. The review process was derived from theoretical pre-considerations that allow conclusions to be drawn on the reviewed literature. Our work can be classified as archival research in the framework proposed by Searcy and Mentzer (2003). The guidelines of Keele (2007) were followed to review and synthesis recent literature relating to the application of EDM and LA in the higher education context.

3.1. Search strategy

Data mining literature in education is grounded by several reference disciplines, including EDM and LA (Papamitsiou and Economides, 2014; Romero and Ventura, 2013). Therefore, the goal in this review was to collect relevant papers to identify what has been done in this area with regards to the research questions. The search period was set from 2000 to 2017. The literature on EDM and LA was grounded to include aspects related to data visual mining, data mining, machine learning, statistic, artificial intelligence, soft-computing, and neural network. We extensively and iteratively searched international databases of authoritative academic resources and publishers, including Scopus, Web of Science, Google Scholar, ERIC, Science Direct, DBLP and ACM Digital Library, IEEE Xplore, Springer Link as well as Conference Proceedings related to data analytics, data mining, and other similar disciplines.

3.1.1. Keywords (search terms)

A number of keywords and combinations were used when searching for the empirical studies on EDM and LA, for example: 'data analytics' OR 'learning analytics', 'educational data mining' OR 'knowledge discovery' OR 'data mining techniques' OR 'artificial intelligence' OR 'artificial neural network' OR 'visual data mining' OR 'classification' OR 'clustering' OR 'association rule and their applications' AND 'higher education' OR 'university context' OR 'LMS' OR 'distance learning' OR 'online learning system'. More details about the search terms used in this review can be found in Appendix (Table I).

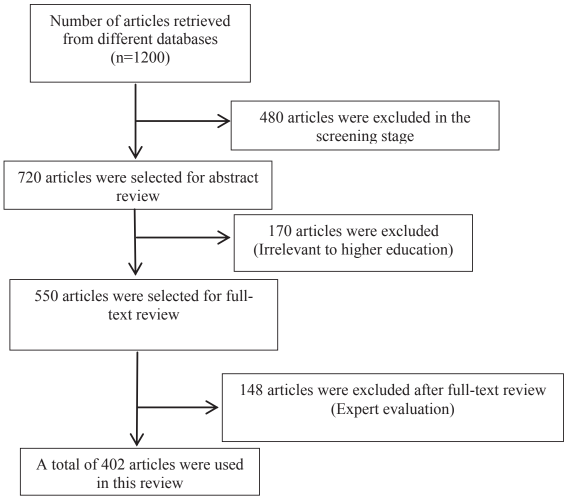


Fig. 2. The selection of previous studies.

3.1.2. Inclusion/exclusion criteria

Fig. 2 shows the process of finalizing the previous studies for this review. The initial stage of the literature search yielded 1200 papers. After subsequent screening of previous works, more technical studies as well as duplicated works were not selected in this review, resulting with 720 papers. Articles listed in ISI and Scopus, and presented empirical results were included. Articles unrelated to educational use of data analytics in the context of higher education, or were not regarded as credible, or of very low quality were excluded. Other theoretical and conceptual articles, essays, tool demonstrations, workshops and books were also excluded. As such, a total of 550 studies were included for the full text review. These studies were further filtered based on the applied method, clarity of the findings, and the degree of underlying innovation. A value of 1–3 was given by two researchers based on meeting the following criteria:

1. Whether the research description related to the use of EDM and LA?
2. Are the techniques clearly described in the text?
3. How relevant is the context and sample to this review (university context)?
4. Can the findings be trusted in answering the research questions?

The quality of each article was assessed and calculated by summing scores on each of the four criteria provided by the researchers (12 scores). An article was considered low (1) when its value was 5 and below; or medium (2) when its value was between 6 and 9; and high (3) when its value was more than 10. The inter-rater reliability (r) result for all the articles was 0.921, which implies a high agreement between the two researchers on the quality of the selected studies for this review. A total of 172 articles were categorized a high quality, 230 articles were categorized as medium quality, and 148 were categorized as low quality. Although the available information in these selected articles were related and within the scope of this review scope, only articles with high and medium scores were included in this work (402).

4. Results

This review is an attempt to shed light on more specific learning problems which previous reviews have not been not been able to address. Most of the previous reviews discussed earlier have not been extensive either in the source coverage or in their breadth of dimensions to provide a fresh and comprehensive view of the entire domain of EDM/LA in higher education. In addition, previous reviews have been based on relatively few studies, whereas the present review exploits some of the recent developments in this field and incorporates more empirical studies.

This section summarizes the literature on the potential of EDM and LA to support processes related to collaborative learning, self-learning, monitoring, evaluation (such as performance, success, dropout and retention), and decision-making. Our review of the literature showed that certain data mining techniques are drawn from a variety of applications which we categorized into four major dimensions: computer-supported learning analytics (CSLA), computer-supported predictive analytics (CSPA), computer-supported behavioral analytics (CSBA), and computer-supported visualization analytics (CSVA): that are widely used in previous works (Baker, 2010; Perera et al., 2009; Romero and Ventura, 2007; Romero and Ventura, 2010; Romero et al., 2008). We used these dimensions to make the review easier to read and follow. This enabled us to cover a rather wider range of aspects or dimensions such as CSVA in general, or dropout and retention in the case of CSPA.

Previous studies on CSLA (120 articles, 30%) concentrated mainly on the use of statistical analysis of data to perform sophisticated analytical tasks in order to analyze students' information-searching and collaborative learning behaviors in a course context. In

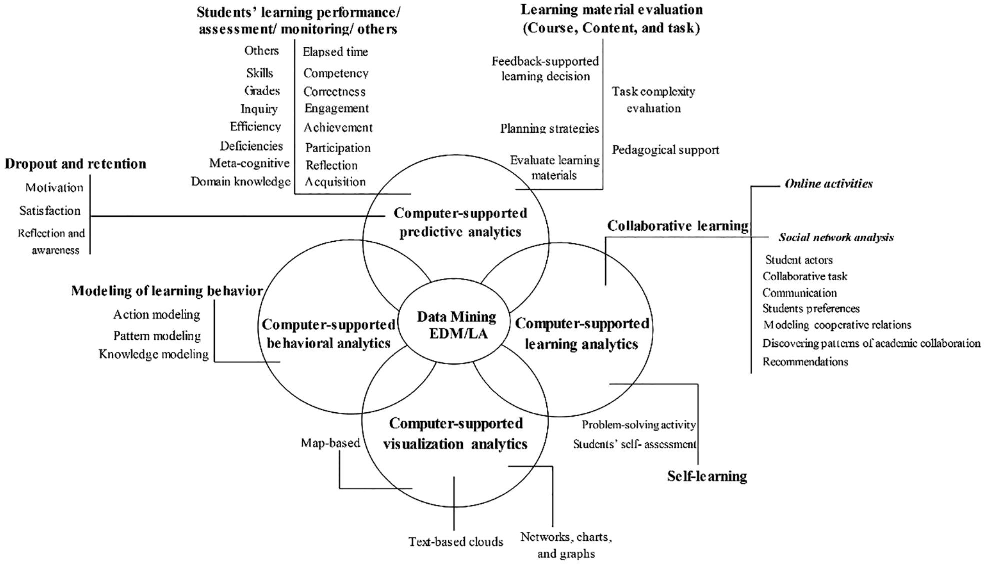


Fig. 3. Data mining schemes in higher education.

addition, the majority of the studies on CSPA (253 articles, 63.25%) focused on the use of predictive functions or continuous variables to suggest effective ways to improve students' learning and performance, as well as evaluating the appropriateness of the learning materials. Most of the studies on the CSBA dimension (80 Articles, 20%) discovered models of student behavior, actions, and knowledge. Other studies on CSVA (38 articles, 9.50%) focused on methods to visually explore data (using interactive graphs), so to highlight useful information and produce accurate and data-informed decisions.

To shed light on more specific learning problems, these four dimensions were divided into several sub-dimensions (see Fig. 3). More specific related problems for each dimension are provided in Appendix Table II. It should also be noted that since these four dimensions are closely related, some references were used for more than one dimension (Table 1).

4.1. Computer-supported learning analytics (CSLA)

In the context of this study, CSLA refers to the use of data mining techniques to derive actionable information based on students' interaction in the LMS environment. Instructors involved in the continuous monitoring of the learning activity are in need for methods to assess interaction among students in a group to identify possible interventions to be taken and evaluate the effectiveness of the course (Retalis et al., 2006). Both EDM and LA are typically applied to identify learning problems by assessing students' interactions and learning results. Data emerged from these assessments can potentially help in estimating or changing the level of support needed for increasing students' self-awareness about the activity and content. For example, LMS data from course-related activities, such as discussion forums, content delivery, and assessment, can be used to associate system level objects with students' preferences. This would also provide an opportunity for the instructor to gain a comprehensive view of possible learning outcomes, as well as discovering undesirable behaviors among students when inappropriate control over the learning process occurs. In addition, the use of EDM/LA to analyze the learning behaviors and student interactions with course resources might eventually facilitate the evaluation of educational effectiveness, and aid the design of intervention strategies to enhance students' cognitive abilities (Vatrapu et al., 2011). This led us to assume that EDM and LA for CSLA are oriented to shape different domains that characterize the collaborative learning, social network analysis, and self-learning behavior (including self-assessment and self-regulated learning). It has the potential to formulate the learning experience of students in a way that meet specific learning requirements or conditions.

4.1.1. Collaborative learning

EDM and LA are commonly used to deal with issues related to providing instructional strategies that supports and enhances the collaboration process among students who work together in small groups. Interaction was the main indicator for measuring the effectiveness of collaboration in VLEs (Agudo-Peregrina et al., 2014) in which the users' activity logs from the learning platform were used as the main tool for inferring learners' activities so that to fit certain behaviors and preferences. For example, Ben-Zadok et al., (2009) demonstrated the potential of using Data Mining (DM) techniques (visual mining tool) for increasing the students' exposure to different subject matter based on data extracted from the log files. This can enable decision makers to assess the students' learning processes and to meet their different learning needs, based on their actual behaviors and preferences. Van Leeuwen et al. (2014) examined the effects of learning analytics functioning as supporting tools on the teachers' way of diagnosing and intervening whilst guiding cooperating groups. Janssen et al. (2007) explored the effects of EDM on students' participation during computer-supported collaborative learning (CSCL) sessions. They visualized which elements enable students to participate more and help them to collaborate better in CSCL. Further, Cerezo et al. (2016) examined patterns of students' interaction with a LMS and their relationship

Table 1
Dimensions of EDM and LA utilization to solve certain learning problems.

Objectives	References	%
CSLA		
Collaborative learning	(Agudo-Peregrina et al., 2014; Akçapýnar et al., 2014; Alves et al., 2015; Anaya and Boticario, 2011; Baruque et al., 2007; Ben-Naim, Marcus, and Bain, 2008; Ben-Zadok et al., 2009; Chamizo-Gonzalez et al., 2015; Cobo, Rocha, and Rodríguez-Hoyos, 2014; Eagle, Johnson, and Barnes, 2012; Gaudioso et al., 2009; Goguadze et al., 2010; Govaerts et al., 2010; He, 2013; Heathcote and Dawson, 2005b; Ingram, 1999; Ji et al., 2016; Kardan and Conati, 2010; Kim et al., 2012; Lile, 2011; Macfadyen and Dawson, 2010; Maldonado et al., 2010; McCuaig and Baldwin, 2012; Mor and Minguillón, 2004; Mostow et al., 2005; Paiva et al., 2016; Perera et al., 2009; Ratnapala et al., 2014; Scheffel et al., 2011; Schrire, 2004; Talavera and Gaudioso, 2004; Vasić et al., 2015; Wang, 2002; Wu and Leung, 2002; Yu, Own, and Lin, 2001; Zaiane, 2001)	30%
Social Network Analysis	(Agustianto et al., 2016; Aher and Lobo, 2013; Anjewierden et al., 2007; Antunes, 2008; Ba-Omar et al., 2007; Chen et al., 2008; Chen and Liou, 2014; Chen and Weng, 2009; Chrysostomou et al., 2009; D'Mello et al., 2010; Farzan and Brusilovsky, 2006; Goldin et al., 2012; Gruzd et al., 2016; Haythornthwaite, 2008; He and Yan, 2015; Heathcote and Dawson, 2005b; Hou, 2011; Hung and Zhang, 2008; Hung et al., 2016; Ingram, 1999; Janssen et al., 2007; Kelly and Tangney, 2005; Köck and Paramythis, 2011; Krištofič, 2005; Kumar and Chadha, 2012; Lee et al., 2007; Little et al., 2011; Macfadyen and Dawson, 2010; Markellou et al., 2005; McKeon, 2009; Minaei-Bidgoli and Tan, 2004; Mochizuki et al., 2003; Nankani et al., 2009; Paiva et al., 2016; Perera et al., 2009; Psaromiligkos et al., 2011; Ratnapala et al., 2014; Shanabrook et al., 2010; Stanca and Felea, 2016; Tang and McCalla, 2005; Ueno, 2004a; Van Leeuwen et al., 2014; Ventura et al., 2008; Viola et al., 2006; Wolpers et al., 2007; Wu and Leung, 2002; Xing et al., 2015; Yim and Warschauer, 2017; Zaíane, 2002; Zakrzewska, 2008; Zhang et al., 2008)	
Self-learning behavior/self-assessment/self-regulated learning	(Aleven et al., 2006; Anaya and Boticario, 2010; Azevedo et al., 2010; Chi et al., 2011; Conati and Vanlehn, 2000; de-la-Fuente-Valentín et al., 2015; Feng and Heffernan, 2006; Gobert et al., 2012; Hou, 2011; Hung et al., 2016; Iglesias-Pradas, Ruiz-de-Azcárate, and Agudo-Peregrina, 2015; Kerr and Chung, 2012; Köck and Paramythis, 2011; Lin et al., 2015; Maldonado et al., 2010; Mochizuki et al., 2003; Muldner et al., 2011; Nesbit et al., 2007; Nussbaumer et al., 2015; Ouyang and Zhu, 2008; Pardo, Han, and Ellis, 2017; Pejić and Molcer, 2016; Robinet et al., 2007; Sabourin, Mott, and Lester, 2012; Stevens et al., 2005; Tsai, Ouyang, and Chang, 2016; Ueno, 2004a, 2004b; Ueno and Nagaoka, 2002; Verbert et al., 2013; You, 2016; Zaiane, 2001; Zukhri and Omar, 2008)	
CSPA		
Learning material evaluation (course content and task)	(Aher and Lobo, 2013; Álvarez et al., 2016; Arroyo et al., 2010; Becker et al., 2000; Bogarin Vega et al., 2016; Bouchet et al., 2012; Cambruzzi et al., 2015; Campagni et al., 2014; Chen and Chen, 2009; Dominguez et al., 2010; Drăgulescu et al., 2015; El-Halees, 2011; Farzan and Brusilovsky, 2006; Figueiredo et al., 2016; Gobert et al., 2012; González-Brenes and Mostow, 2010; Grobelnik et al., 2002; Heathcote and Dawson, 2005a; Hershkovitz and Nachmias, 2011; Holzhüter et al., 2013; Hsu et al., 2011; Ingram, 1999; Jiang et al., 2016; Jovanović et al., 2007; Kerr and Chung, 2012; Li et al., 2015; Little et al., 2011; Lu et al., 2007; Ma et al., 2000; Mac Kim and Calvo, 2010; Macfadyen and Dawson, 2010; Macfadyen and Sorenson, 2010; Manek et al., 2016; Mankad, 2016; Mazza and Dimitrova, 2004; Minaei-Bidgoli and Tan, 2004; Nakamura et al., 2015; Onan et al., 2016; Pardo et al., 2016; Pechenizkiy et al., 2008; Pejić and Molcer, 2016; Romero et al., 2004; Romero et al., 2013; Rupp et al., 2012; Sakurai et al., 2012; Schönbrunn and Hilbert, 2007; Selmoune and Alimazighi, 2008; Shen et al., 2003; Shi et al., 2012; Shih et al., 2010; Su et al., 2008; Tang et al., 2000; Tang and McCalla, 2002; Trivedi et al., 2012; Tsai et al., 2016; Ventura et al., 2008; Wang et al., 2008; Wong and Li, 2016; Zaiane, 2001)	63.25%
Students' learning evaluation/assessment/monitoring	(Agudo-Peregrina et al., 2014; Agustianto et al., 2016; Ahmed and Elaraby, 2014; Al-Radaideh et al., 2006; Ali et al., 2013; Andrejko et al., 2007; Azevedo et al., 2010; Baker et al., 2008; Baker and Gowda, 2010; Baradwaj and Pal, 2012; Barker-Plummer et al., 2012; Barracosa and Antunes, 2010; Beheshti et al., 2012; Beikzadeh and Delavari, 2005; Ben-Zadok et al., 2009; Bergner et al., 2012; Bhardwaj and Pal, 2012; Bolt and Newton, 2011; Bouchet et al., 2012; Bresfelean et al., 2008; Bunkar et al., 2012; Cai et al., 2011; Campagni et al., 2014; Casey and Azcona, 2017; Cen et al., 2007; Cerezo et al., 2016; Cetintas et al., 2014; Chalaris et al., 2015; Chamizo-Gonzalez et al., 2015; Chen et al., 2007; Chen et al., 2008; Cocea and Weibelzahl, 2007; Crespo and Antunes, 2012; de-la-Fuente-Valentín et al., 2015; DeBerard et al., 2004; Delavari et al., 2005; Dringus and Ellis, 2005; Elias and MacDonald, 2007; Falakmasir and Habibi, 2010; Feng and Beck, 2009; Finnegan et al., 2008; Forsyth et al., 2012; France et al., 2010; Frey and Seitz, 2011; García et al., 2007; Gobert et al., 2015; Gobert et al., 2013; Gobert et al., 2012; Golding and Donaldson, 2006; Gong and Beck, 2010; Gong et al., 2010; Guleria et al., 2014; Hämäläinen and Vinni, 2006; Hardof-Jaffe et al., 2010; Heathcote and Dawson, 2005a, 2005b; Hernándeza et al., 2006; Hershkovitz and Nachmias, 2008; Hien and Haddawy, 2007; Huang et al., 2006; Huang et al., 2007; Hussaan and Sehaba, 2014; Ibrahim and Rusli, 2007; Iglesias-Pradas et al., 2015; Jeong and Biswas, 2008; Jo et al., 2017; Johnson and Barnes, 2010; Joshi et al., 2016; Kaur and Singh, 2016; Kerr and Chung, 2012; Kobrin et al., 2012; Koprinska, 2010; Kordík and Kuznetsov, 2015; Kotsiantis and Pintelas, 2005; Kovanović et al., 2015; Kumar and Chadha, 2012; Lee and Brunskill, 2012; Leong et al., 2012; Li et al., 2015; Liu et al., 2010; Lopez et al., 2012; Lykourentzou et al., 2009; Macfadyen and Dawson, 2010; Macfadyen and Sorenson, 2010; Maldonado et al., 2010; Marbouti et al., 2016; Martínez Abad and Chaparro Caso López, 2017; Martinez, 2001; Mazza and Dimitrova, 2004; McCuaig and Baldwin, 2012; Mcdonald, 2004; Mochizuki et al., 2003; Molina et al., 2012; Myller et al., 2002;	

(*continued on next page*)

Table 1 (*continued*)

Objectives	References	%
	Nasiri and Minaei, 2012; Nebot et al., 2006; Nesbit et al., 2007; Nugent et al., 2009; Nwaigwe and Koedinger, 2010; Ogor, 2007; Oladokun et al., 2008; Pai et al., 2010; Pandey and Pal, 2011; Parack et al., 2012; Pardo et al., 2017; Pardo et al., 2016; Pardos and Heffernan, 2010; Pardos et al., 2007; Pardos et al., 2008; Pardos et al., 2014; Pardos et al., 2012; Parmar et al., 2015; Patil and Kumar, 2017; Pechenizkiy et al., 2008; Pedro et al., 2013; Pradeep et al., 2015; Pritchard and Warnakulasooriya, 2005; Rai and Beck, 2010; Rajeswari and Lawrance, 2016; Rau and Pardos, 2012; Rau and Scheines, 2012; Cristobal Romero et al., 2013; Romero et al., 2013; Romero et al., 2004; Romero et al., 2008; Sabourin et al., 2012; Sakurai et al., 2012; Salas et al., 2016; Schrire, 2004; Sembiring et al., 2011; Serrano-Laguna et al., 2012; Shaleena and Paul, 2015; Shangping and Ping, 2008; Shi et al., 2012; Shovon and Haque, 2012; Silva et al., 2016; Simpson, 2006; Stamper et al., 2012; Stanca and Felea, 2016; Stevens et al., 2005; Suganya and Narayani, 2017; Sun, 2010; Sweeney et al., 2015; Tan, 2012; Tang and McCalla, 2002; Thai-Nghe et al., 2010; Tovar and Soto, 2010; Trivedi et al., 2010; Ueno, 2004; Vasić et al., 2015; Vranic et al., 2007; Wang and Mitrovic, 2002; Wang and Beck, 2012; Wong and Li, 2016; Wu, 2010; Xing et al., 2015; Xiong et al., 2010; Xiong and Pardos, 2011; Xu and Mostow, 2010; Yoo et al., 2006; You, 2016; Yudelson et al., 2010; Yudelson et al., 2010; Zafra and Ventura, 2009; Zhang et al., 2007; Zhang, 2010; Zheliazkova et al., 2015; Zukhri and Omar, 2008)	
Dropout and retention	(Baradwaj and Pal, 2012; Bayer, Bydzovská, Géryk, Obsivac, and Popelinsky, 2012; Cambruzzi et al., 2015; Carter and Yeo, 2016; Cocea and Weibelzahl, 2006; de-la-Fuente-Valentín et al., 2015; de Almeida Neto and Castro, 2015; Dejaeger, Goethals, Giangreco, Mola, and Baesens, 2012; Govaerts et al., 2010; Iam-On and Boongoen, 2017; Lin, 2012; Lonn, Aguilar, and Teasley, 2015; Lykourentzou et al., 2009; Márquez-Vera et al., 2016; Mazza and Dimitrova, 2004; Morris, Wu, and Finnegan, 2005; Nandeshwar, Menzies, and Nelson, 2011; Pradeep et al., 2015; Rad, Naderi, and Soltani, 2011; Romero et al., 2004; Shaleena and Paul, 2015; Thomas and Galambos, 2004; Yu, DiGangi, Jannasch-Pennell, and Kaprolet, 2010)	
CSBA - Decision modeling (Data-driven decision-making) ● map-based, ● text-based ● networks, ● charts and graphs	(Alfonseca et al., 2007; Álvarez et al., 2016; Amershi and Conati, 2009; Anaya and Boticario, 2011; Anjewierden et al., 2007; Antonenko et al., 2012; Ayers et al., 2009; Ayesha et al., 2010; Bakar et al., 2006; Baker et al., 2008; Bansal et al., 2016; Beck and Woolf, 2000; Beikzadeh and Delavari, 2005; Blagojević and Micić, 2013; Bogarin Vega et al., 2016; Bouchet et al., 2012; Buldu and Üçgün, 2010; Caputi and Garrido, 2015; Casey and Azcona, 2017; Castro et al., 2005; Cerezo et al., 2016; Chang et al., 2006; Chen and Liou, 2014; Cobo et al., 2014; Cobo et al., 2010; Cruz-Benito et al., 2015; D'Mello and Graesser, 2010; D'Mello et al., 2010; Desmarais and Gagnon, 2006; El-Halees, 2009; García-Saiz and Zorrilla, 2010; García et al., 2007; Goguadze et al., 2010; Goyal and Vohra, 2012; Griffiths and Graham, 2009; Hung and Zhang, 2008; Iam-On and Boongoen, 2017; Jo et al., 2017; Kardan and Conati, 2010; Kinnebrew and Biswas, 2011; Kobrin et al., 2012; Lee, 2007; Li et al., 2010; Lin, 2012; Malmberg et al., 2013; Mankad, 2016; Marbouti et al., 2016; McCuaig and Baldwin, 2012; Nesbit et al., 2008; Nesbit et al., 2007; Paiva et al., 2016; Parack et al., 2012; Pardos et al., 2014; Patarapichayatham et al., 2012; Psaromiligkos et al., 2011; Qiu et al., 2010; Rai et al., 2009; Ritter et al., 2009; Romero et al., 2010; Romero et al., 2004; Shanabrook et al., 2010; Shen et al., 2003; Siemens and Long, 2011; Sisovic et al., 2016; Stanca and Felea, 2016; Sweet and Rupp, 2012; Talavera and Gaudioso, 2004; Tang and McCalla, 2002, 2005; Tsai et al., 2016; Ueno, 2004; Viola et al., 2006; Wang and Shao, 2004; Wolpers et al., 2007; Wong and Li, 2016; Xu and Mostow, 2010; Yoo et al., 2006; Yu et al., 2008; Zakrzewska, 2008; Zheliazkova et al., 2015)	20%
CSVA ● Decision modeling (Data-driven decision-making) ● map-based, ● text-based ● networks, ● charts and graphs	(Álvarez et al., 2016; Barnes, 2005; Beikzadeh and Delavari, 2005; Caputi and Garrido, 2015; Chen et al., 2008; Cruz-Benito et al., 2015; Dejaeger et al., 2012; Delavari et al., 2005; Delavari et al., 2008; Hwang, 2008; Jin et al., 2009; Kiang et al., 2009; Kumar and Chadha, 2012; Lau et al., 2007; Lee et al., 2009; Li et al., 2015; Lin et al., 2015; Little et al., 2011; Liu et al., 2010; Lonn et al., 2015; McKeon, 2009; Nankani et al., 2009; Paiva et al., 2016; Parmar et al., 2015; Pradeep et al., 2015; Rad et al., 2011; Cristobal Romero et al., 2013; Romero et al., 2013; Scheffel et al., 2011; Schönbrunn and Hilbert, 2007; Serrano-Laguna et al., 2012; Sun, 2010; Tovar and Soto, 2010; Tseng et al., 2007; Vatrapu et al., 2011; Wu, 2010; Yoo and Cho, 2012; Zadrozny and Elkan, 2001).	9.50%

Note that some papers used more than one method, and thus they are classified for more than one dimension.

with achievement using students' data from Moodle. These practices were claimed to help the instructor to better understand the various learning characteristics of students, thus helping them identify at-risk students.

4.1.2. Social network analysis

Networked learning benefits from the utilization of technology to establish connections between students, instructors, communities, and resources (Ferguson and Shum, 2012). The use of EDM and LA for social networks analysis has been reported to be associated with individuals' learning and how they can build knowledge together in cultural and social settings. This includes discovering patterns of academic collaboration, assessment, active communication, recommendations and several more. For example, Duval (2011) clarified that by collecting data about user behavior, LA can be useful for providing recommendations about learning resources and activities. In addition, the literature showed that mining students' online social interaction is important for recommending appropriate learning partners in a web-based cooperative learning environment (Chen et al., 2008). Furthermore, both EDM and LA have been extensively applied in this contexts to aid educational decision makers to take the appropriate actions for a given learning task (Nankani et al., 2009). This was believed to provide the necessary support for aiding the learning process by providing the environment to share and collaborate with other team members (Heathcote and Dawson, 2005b).

4.1.3. Self-learning behavior

It is common that engaging students in a self-learning experience allow them to control, observe, evaluate, plan and improve the learning process, and regulate their behavior and context, as well as increase their motivation to learn complex concepts (Nussbaumer et al., 2015). In addition, understanding students' self-regulated learning behaviors such as goal setting and monitoring have been found to be crucial to the students' success in an online learning environment (Sabourin et al., 2012), where students' are expected to use specific strategies for achieving their goals. Thus, EDM and LA can play a key role for prompting students to use the relevant strategies (Winne and Baker, 2013). A study by Conati and Vanlehn (2000) used EDM to promote students' regulation of learning processes to self-explain complex concepts by examining the produced justifications in alignment to the learning goals. Aleven et al. (2006) used EDM to examine the self-regulated learning behaviors within learning systems based on students' progress in a problem-solving task. Other studies such as Sabourin et al. (2012) applied EDM to predict how learners transform their mental abilities into academic skills based on evidence of goal-setting and monitoring activities. From these studies, it can be surmised that the applications of EDM and LA provided a promising solution to the online self-learning environment by investigating students' usage of learning resources and self-evaluation exercises and it's possible impact on their performance (Papamitsiou and Economides, 2014).

4.2. Computer supported predictive analytics (CSPA)

When it comes to understanding the main antecedents for promoting students' learning, EDM and LA can be used to predict students' performance and retention in particular course(s) based on the assessment and the evaluation of their achievement, participation, engagement, acquiring, grades, and domain knowledge in a learning activity. This include an evaluation of learning materials to assess the task complexity, and provide feedback to support decision learning by planning for new strategies that enhance the overall learning outcomes (Sembiring et al., 2011). Luan (2002) indicated that by using data mining techniques in a learning context can help in the discovery of knowledge and hidden patterns within large amounts of data and making predictions for outcomes or behaviors. Baradwaj and Pal (2012) declared that EDM and LA can be used to discover knowledge that helps instructors to identify early dropouts among students and to determine who needs special attention. Our review of the literature on EDM and LA for prediction related problems found that the application of data mining (EDM and LA) in higher education has the potential to enhance the current teaching and learning experiences by evaluating the interaction between learning materials, students' participation levels, and students' dropout and retention.

4.2.1. Learning material evaluation

Data mining has been reported to provide a sufficient way for analyzing and investigating LMS data to help in enhancing the learning materials and the quality of higher education system. According to Bunkar et al. (2012), data mining can be used to study the main attributes that may affect the student performance in courses based on their interaction with the course. EDM and LA are commonly used to study the effects of different pedagogical supports provided to the learners (Jeong and Biswas, 2008). It can be applied to educational databases to construct coursework, plan, and schedule classes (Romero and Ventura, 2010). Other previous studies developed educational models to predict how learning materials might be designed to fit the knowledge of the student. Pejić and Molcer (2016) stated that EDM and LA can be used to help learners determine their learning needs by adjusting the complexity of a learning task. Many studies applied LA to help course designer, instructors, and institutions in decision-making by providing supportive feedback and helping instructors to understand how their students react to them, thus assessing course effectiveness (Retalis et al., 2006). Furthermore, EDM can be also used to support a learner's reflections and provide positive feedback to learners (Merceron and Yacef, 2005), which can be used in the development of strategies, particularly to improve students' learning performance (Manek et al., 2016).

4.2.2. Evaluation, assessment, and monitoring of students' learning

The evaluation and monitoring practices of students learning is considered as an essential aspect in higher education (Dekker et al., 2009). Performance monitoring includes assessments and evaluation processes, which play a vital role in providing valuable information that help students, instructor, administrators, and policy makers in higher education institutions to make decisions. The changing factors in contemporary education has led to the use of various data mining techniques to monitor student performance which offers various investigation methods to analyze and discover hidden information in educational systems (Ogor, 2007). The data extracted by such systems continuously comprise the score for certain learning goals so to generate grades, elapsed times for the learner interactions with the LMS activities. According to Parack et al. (2012), data mining can be used to identify students, behavior and the pattern in which they learn, and to find undesirable behavior and perform student profiling. In addition, the common goal for applying EDM and LA to the data produced by LMS is to predict student achievement. For example, Bunkar et al. (2012) applied data mining for predicting the fail and pass ratio among students based on their final grade. Ben-Zadok et al. (2009), used EDM and LA to analyze students' learning behavior to warn those at risk before their final grades. Romero et al. (2013) proposed the use of data mining mainly to improve the prediction of students' final performance based on their participation in on-line discussion forums.

Salas et al. (2016) used LA to support the acquisition of scientific skills by analyzing students' behavior and creating clusters according to their performance during the formulation of scientific questions. Such practice was found to support the process of determining strategies to strengthen the scientific competences of students. Peckham and McCalla (2012) described how data mining can be used to identify positive and negative cognitive skills essential for reading acquisition. The authors used the information gathered from the students' interactions to provide the necessary aid for students to improve their *meta*-cognitive skills. In addition, Xing et al. (2015) used LA to solve the problem of predicting students' performance in a computer supported collaborative learning environment based on the use of EDM and LA applications.

4.2.3. Dropout and retention

The number of students dropping out from online courses has been growing. This led many researchers to examine the factors that inhibits students' performance at various educational levels. Although there is a wide range of tools to predict students' dropout intention, there is still no consensus about the best ways to understand the changing nature of this phenomenon regardless of the pedagogical style or activity used in the course. For example, Pradeep et al. (2015) used EDM to study and analyze the factors affecting students' academic performance, which contributed to the prediction of their failure and dropout. Using this technique allowed them to identify weak students shown to have poor performance in their academics. Cambruzzi et al. (2015), on the other hand, used LA to contain dropout rates based on a set of pedagogical actions in distance education courses. They reported a high predictability of students' dropout status with an average of 87% accuracy and an average reduction of 11% in dropout rates. In addition, Dekker et al. (2009) used EDM for predicting the students dropout rate at two different academic institutes after the first semester of their studies in which they found that predictions of early dropouts are most useful for identifying and assisting failing students as well as identifying the success-factors specific to the course content. While Bayer et al (2012) applied EDM to predict dropouts when student data has been enriched with data derived from students' social behavior.

4.3. Computer-supported behavioral analytics (CSBA)

The utilization of data mining techniques can yield considerable insights and reveal valuable patterns in students' learning behaviors (He, 2013). Hung and Zhang (2008) used data mining to identify students' behavioral patterns and preferences when participating in online learning activities. They found that using EDM and LA resulted in improving students' learning experience when collaborating at a distance. Currently, most of the focus on EDM and LA concentrates on the use of real-time data to regulate the learning of new information so that students can solve problems with varied levels of complexity. For example, Jeong and Biswas (2008) designed a student model for predicting certain learning processes by incorporating information about students' knowledge, motivation, metacognition, and attitudes. According to Romero et al. (2010), EDM could be used to detect irregular student behavior and activities in an online environment such as Moodle by evaluating the relation between students online activities and their final marks. In addition, McCuaig and Baldwin (2012) applied EDM in order to identify successful learners based on their interaction behavior. The reported that log data generated from the LMS could be mined to predict the students' performance in e-learning course (success or failure) without the need for formal assessments results.

4.4. Computer-supported visualization analytics (CSVA)

CSVA is a form of inquiry that combines information visualization techniques with advances in data mining and knowledge representation, mainly to offer a visual analysis of individuals' behaviors with respect to the activity. In educational settings, CSVA focuses on the use of visualization tools to provide insights into the learning process and students' experiences (Peña-Ayala,2014). For instance, mapping online discussions, and evaluating the quality of each single post (engagement) based on the structural characteristics of the subject can help students identify the relevant posts and discussions. According to Jin et al. (2009), visual data mining used in a higher education evaluation system can make the evaluation method more flexible, more diverse and more visual in which the efficiency of the learning processes can be improved. Kumar and Chadha (2011), on the other hand, addressed the potential of using EDM to extract meaningful knowledge and information from large data sets and use this information to discover hidden patterns and relationships that can be useful for the decision-making process of higher education. Graphs can be used to represent students' engagement with the learning task that can help instructors gain a better understanding of their students' online behavior and become mindful of what is happening in the online environment (Romero et al., 2008). Furthermore, data visualization tools can be used in higher education to simplify complex data and to track students' multi-dimensional data captured from their interaction with online educational systems (Romero and Ventura, 2007).

5. Data mining techniques

Generally, modern data mining techniques look for new patterns in data and develops new algorithms and/or new models, while learning analytics applies known predictive models in instructional systems (Prakash et al., 2014). This section describes the application of different data mining techniques used in the higher education sector in an attempt to answer the second research question. Data mining techniques were grouped in accordance with the focus of this study. We identified twelve techniques (see Table 2): classification (26.25%), clustering (21.25%), visual data mining (15%), statistics (14.25%), association rule mining (14%), regression (10.25%), sequential pattern mining (6.50%), text mining (4.75%), correlation mining (3%), outlier detection (2.25%), causal mining (1%), and density estimation (1%).

Table 2
The application of data mining techniques in higher education.

Techniques	Authors	%
Classifications	(Agudo-Peregrina et al., 2014; Agustianto et al., 2016; Ahmed and Elaraby, 2014; Al-Radaideh et al., 2006; Amershi and Conati, 2009; Anjewierden et al., 2007; Arroyo et al., 2010; Azevedo et al., 2010; Baker et al., 2008; Baradwaj and Pal, 2012; Bayer et al., 2012; Beheshti et al., 2012; Beikzadeh and Delavari, 2005; Bhardwaj and Pal, 2012; Blagojević and Micić, 2013; Bolt and Newton, 2011; Bunkar et al., 2012; Cai et al., 2011; Casey and Azcona, 2017; Cetintas et al., 2014; Chang et al., 2006; Cobo et al., 2014; Cocea and Weibelzahl, 2006, 2007; Conati and Vanlehn, 2000; Dejaeger et al., 2012; Delavari et al., 2005; Desmarais and Gagnon, 2006; Drăgulescu et al., 2015; El-Halees, 2009, 2011; Falakmasir and Habibi, 2010; Frey and Seitz, 2011; García et al., 2007; Gobert et al., 2015; Gobert et al., 2012; Goguadze et al., 2010; Guleria et al., 2014; Hämäläinen and Vinni, 2006; Hershkovitz and Nachmias, 2008; Hien and Haddawy, 2007; Hussaan and Sehaba, 2014; Ibrahim and Rusli, 2007; Ji et al., 2016; Kaur and Singh, 2016; Kerr and Chung, 2012; Kim et al., 2012; Kohli and Birla, 2016; Lee and Brunskill, 2012; Lee et al., 2007; Lopez et al., 2012; Lykourentzou et al., 2009; Macfadyen and Dawson, 2010; Manek et al., 2016; Mankad, 2016; Márquez-Vera et al., 2016; Martínez Abad et al., 2017; McCuaig and Baldwin, 2012; Molina et al., 2012; Morris et al., 2005; Nandeshwar et al., 2011; Nankani et al., 2009; Ogor, 2007; Oladokun et al., 2008; Pai et al., 2010; Paiva et al., 2016; Pandey and Pal, 2011; Pardo et al., 2016; Pardos and Heffernan, 2010; Pardos et al., 2007; Pardos et al., 2008; Pardos et al., 2014; Parmar et al., 2015; Patil and Kumar, 2017; Pechenizkiy et al., 2008; Pedro et al., 2013; Pejić and Molcer, 2016; Pradeep et al., 2015; Qiu et al., 2010; Rajeswari and Lawrance, 2016; Rau and Pardos, 2012; Cristobal Romero et al., 2013; Romero et al., 2013; Romero et al., 2008; Rupp et al., 2012; Sabourin et al., 2012; Scheffel et al., 2011; Schrire, 2004; Sembiring et al., 2011; Shaleena and Paul, 2015; Shovon and Haque, 2012; Stamper et al., 2012; Stanca and Felea, 2016; Stevens et al., 2005; Sun, 2010; Thai-Nghe et al., 2010; Vasić et al., 2015; Wang and Mitrovic, 2002; Xing et al., 2015; Xiong et al., 2010; Xiong and Pardos, 2011; Yu et al., 2010; Yu et al., 2008; Yudelson et al., 2010)	26.25%
Clustering	(Aher and Lobo, 2013; Akçapýnar et al., 2014; Alfonseca et al., 2007; Amershi and Conati, 2009; Anaya and Boticario, 2010, 2011; Antonenko et al., 2012; Ayers et al., 2009; Ayesha et al., 2010; Baker and Gowda, 2010; Barker-Plummer et al., 2012; Beikzadeh and Delavari, 2005; Bogarin Vega et al., 2016; Bouchet et al., 2012; Bresfelean et al., 2008; Brown et al., 2015; Campagni et al., 2014; Cerezo et al., 2016; Chen et al., 2007; Chen and Liou, 2014; Chrysostomou et al., 2009; Cobo et al., 2010; Cruz-Benito et al., 2015; Dominguez et al., 2010; Eagle et al., 2012; El-Halees, 2009; Figueiredo et al., 2016; Gaudioso et al., 2009; Gong et al., 2010; Hernándeza et al., 2006; Hershkovitz et al., 2011; Hershkovitz and Nachmias, 2008, 2011; Hou, 2011; Hung et al., 2016; Iam-On and Boongoen, 2017; Kardan and Conati, 2010; Kerr and Chung, 2012; Kiang et al., 2009; Köck and Paramythis, 2011; Kohli and Birla, 2016; Kovanović et al., 2015; Lopez et al., 2012; Lu et al., 2007; Luan, 2002; Mac Kim and Calvo, 2010; Maldonado et al., 2010; Malmberg et al., 2013; Myller et al., 2002; Nugent et al., 2009; Nugent et al., 2010; Parack et al., 2012; Pardo et al., 2017; Pardos et al., 2012; Patarapichayatham et al., 2012; Patil and Kumar, 2017; Pechenizkiy et al., 2008; Perera et al., 2009; Rad et al., 2011; Ratnapala et al., 2014; Ritter et al., 2009; Romero et al., 2003; Sakurai et al., 2012; Salas et al., 2016; Shih et al., 2010; Shovon and Haque, 2012; Siemens and Long, 2011; Sisovic et al., 2016; Sparks et al., 2012; Su et al., 2008; Sweet and Rupp, 2012; Talavera and Gaudioso, 2004; Tang et al., 2000; Tang and McCalla, 2002, 2005; Thomas and Galambos, 2004; Trivedi et al., 2012; Vasić et al., 2015; Vranic et al., 2007; Wang and Shao, 2004; Wu, 2010; Xing et al., 2015; Zakrzewska, 2008; Zhang et al., 2007; Zukhri and Omar, 2008)	21.25%
Visual data mining	(Anjewierden et al., 2007; Ben-Naim et al., 2008; Ben-Zadok et al., 2009; Chamizo-Gonzalez et al., 2015; de-la-Fuente-Valentín et al., 2015; Govaerts et al., 2010; Heathcote and Dawson, 2005; Janssen et al., 2007; Little et al., 2011; Macfadyen and Dawson, 2010; Mazza and Dimitrova, 2004; McKeon, 2009; Mochizuki et al., 2003; Mostow et al., 2005; Nankani et al., 2009; Paiva et al., 2016; Scheffel et al., 2011; Talavera and Gaudioso, 2004; Ueno, 2004; Verbert et al., 2013; Wolpers et al., 2007; Álvarez et al., 2016; Ankerst, 2001; Asha and Chellappan, 2011; Cambruzzi et al., 2015; Caputi and Garrido, 2015; Chen et al., 2008; De Oliveira and Levkowitz, 2003; Duval, 2011; Fayyad et al., 2002; García-Saiz and Zorrilla, 2010; Hwang, 2008; Jeong and Biswas, 2008; Jin et al., 2009; Johnson and Barnes, 2010; Joshi et al., 2016; Jovanović et al., 2007; Keim, 1997, 2002; Keim et al., 2010; Kordík and Kuznetsov, 2015; Lau et al., 2007; Lee et al., 2009; Li et al., 2015; Li et al., 2015; Lonn et al., 2015; Macfadyen and Sorenson, 2010; Pardos and Heffernan, 2010; Rad et al., 2011; Romero et al., 2008; Serrano-Laguna et al., 2012; Sun, 2010; Trivedi et al., 2010; Tseng et al., 2007; Vaitsis et al., 2014; Vatrapu et al., 2011; Wong and Li, 2016; Wu, 2010; Yoo et al., 2006; Zaiane et al., 1998)	15%
Statistics	(Aleven et al., 2006; Ali et al., 2013; Alves et al., 2015; Antonenko et al., 2012; Arroyo et al., 2010; Barker-Plummer et al., 2012; Bolt and Newton, 2011; Cai et al., 2011; Carter and Yeo, 2016; Chalaris et al., 2015; Chamizo-Gonzalez et al., 2015; Chen et al., 2008; Crespo and Antunes, 2012; Cruz-Benito et al., 2015; DeBerard et al., 2004; Dominguez et al., 2010; Farzan and Brusilovsky, 2006; Feng and Heffernan, 2006; Field, 2009; Griffiths and Graham, 2009; Gruzd et al., 2016; Hand, 1998; Haythornthwaite, 2008; Heathcote and Dawson, 2005a, 2005b; Hershkovitz and Nachmias, 2011; Hill et al., 2006; Hung and Zhang, 2008; Iglesias-Pradas et al., 2015; Ingram, 1999; Jeong and Biswas, 2008; Joshi et al., 2016; Kobrin et al., 2012; Lin, 2012; Lin et al., 2015; Lonn et al., 2015; Mac Kim and Calvo, 2010; Macfadyen and Dawson, 2010; Morris et al., 2005; Nussbaumer et al., 2015; Pahl and Donnellan, 2002; Pardo et al., 2017; Patarapichayatham et al., 2012; Rai and Beck, 2010; Rayward-Smith, 2007; Romero et al., 2013; Rupp et al., 2012; Sembiring et al., 2011; Simpson, 2006; Sweet and Rupp, 2012; Tabachnick and Fidell, 2007; Tan, 2012; Tovar and Soto, 2010; Van Leeuwen et al., 2014; Wu and Leung, 2002; You, 2016; Zheliazkova et al., 2015)	14.25%
Association rule mining	(Aher and Lobo, 2013; Baruque et al., 2007; Becker et al., 2000; Beikzadeh and Delavari, 2005; Buldu and Üçgün, 2010; Chen and Chen, 2009; Chen and Liou, 2014; Chen and Weng, 2009; de Almeida Neto and Castro, 2015; Delavari et al., 2008; Dominguez et al., 2010; El-Halees, 2009; Hardof-Jaffe et al., 2010; Huang et al., 2007; Hwang, 2008; Kardan and Conati, 2010; Kohli and Birla, 2016; Kumar and Chadha, 2012; Lee et al., 2009; Li et al., 2010; Lile, 2011; Liu et al., 2010; Ma et al., 2000; Markellou et al., 2005; Minaei-Bidgoli and Tan, 2004; Nebot et al., 2006; Ogor, 2007; Onan et al., 2016; Parack et al., 2012; Pechenizkiy et al., 2008; Psaromiligkos et al., 2011; Retalis et al., 2006; Romero et al., 2010; Romero et al., 2004; Romero et al., 2003; Romero et al., 2013; Schönbrunn and Hilbert, 2007; Selmoune and Alimazighi, 2008; Shangping and Ping, 2008; Shen et al., 2003; Shi et al., 2012; Silva, 2002; Tsai et al., 2016; Tseng	14%

(*continued on next page*)

Table 2 (*continued*)

Techniques	Authors	%
	et al., 2007; Ventura et al., 2008; Vranic et al., 2007; Wang, 2002; Wang and Shao, 2004; Wang et al., 2008; Yoo et al., 2006; Yoo and Cho, 2012; Yu et al., 2001; Zafra and Ventura, 2009; Zaiane, 2001; Zaíane, 2002; Zhang, 2010)	
Regression	(Beck and Woolf, 2000; D'Mello and Graesser, 2010; Elias and MacDonald, 2007; Feng and Beck, 2009; Feng et al., 2009; Finnegan et al., 2008; Forsyth et al., 2012; Goldin et al., 2012; Golding and Donaldson, 2006; Gong and Beck, 2010; González-Brenes and Mostow, 2010; Holzhüter et al., 2013; Jiang et al., 2016; Jo et al., 2017; Kelly and Tangney, 2005; Kobrin et al., 2012; Koprinska, 2010; Kotsiantis and Pintelas, 2005; Lee et al., 2007; Macfadyen and Dawson, 2010; Martinez, 2001; Muldner et al., 2011; Myller et al., 2002; Nasiri and Minaei, 2012; Nwaigwe and Koedinger, 2010; Pardos et al., 2012; Pedro et al., 2013; Rau and Scheines, 2012; Sabourin et al., 2012; Silva et al., 2016; Stanca and Felea, 2016; Sweeney et al., 2015; Tang and McCalla, 2002; Thomas and Galambos, 2004; Tovar and Soto, 2010; Trivedi et al., 2010; Wang and Beck, 2012; Xu and Mostow, 2010a, 2010b; Yu et al., 2008; Yudelson et al., 2010)	10.25%
Sequential pattern mining	(Andrejko et al., 2007; Antunes, 2008; Ba-Omar et al., 2007; Barracosa and Antunes, 2010; Bouchet et al., 2012; Chi et al., 2011; D'Mello et al., 2010; Hung and Zhang, 2008; Kardan and Conati, 2010; Kinnebrew and Biswas, 2011; Krištofič, 2005; Maldonado et al., 2010; Mor and Minguillón, 2004; Nakamura et al., 2015; Nesbit et al., 2008; Nesbit et al., 2007; Ouyang and Zhu, 2008; Perera et al., 2009; Robinet et al., 2007; Shanabrook et al., 2010; Shangping and Ping, 2008; Tang and McCalla, 2002; Vanzin et al., 2005; Zhang et al., 2008)	6.50%
Text mining	(Bari and Benzater, 2005; Chen, Li, and Jia, 2005; Chen et al., 2008; Dringus and Ellis, 2005; El-Halees, 2009; Gobert et al., 2013; Grobelnik et al., 2002; He, 2013; He and Yan, 2015; Hsu et al., 2011; Huang et al., 2006; Lau et al., 2007; Leong et al., 2012; Mochizuki et al., 2003; Tane, Schmitz, and Stumme, 2004; Ueno, 2004a; Wong and Li, 2016; Yim and Warschauer, 2017; Zaiane, 2001)	4.75%
Correlation mining	(Barnes, 2005; Chen and Chen, 2009; France et al., 2010; Koprinska, 2010; Lee, 2007; Mcdonald, 2004; Pritchard and Warnakulasooriya, 2005; Rai and Beck, 2010; Rai and Beck, 2010; Rai et al., 2009; Rayward-Smith, 2007; Viola et al., 2006)	3%
Outlier detection	(Bakar et al., 2006; Bansal et al., 2016; Castro et al., 2005; Goyal and Vohra, 2012; Patil and Kumar, 2017; Suganya and Narayani, 2017; Ueno, 2004b; Ueno and Nagaoka, 2002)	2.25%
Causal data mining	(Caputi and Garrido, 2015; Parack et al., 2012)	1%
Density estimation	(Sakurai et al., 2012; Zadrozny and Elkan, 2001)	1%

Note that some papers used more than one method, and thus they can be found in more than one dimension.

5.1. Classification

Classification is the most commonly applied data mining technique in higher education. It is the process of supervised learning that maps data into different predefined classes. The concepts of classification have been used for predicting student performance, achievement, knowledge, predicting/preventing student dropout, detecting problematic student's behavior in online courses/e-learning. Al-Radaideh et al. (2006) indicated that classification techniques can help in enhancing the quality of the higher educational system by accurately predicting students' final grade in a specific course. This includes 1) examining participation levels in order to prevent students' dropout from distance learning and e-learning courses (Kotsiantis et al., 2003; Lykourentzou et al., 2009), 2) assessing students' engagement with the learning activity (Cocea and Weibelzahl, 2007), 3) continuously assessing students' learning performance (Agapito et al., 2009; Bhardwaj and Pal, 2012), 4) identifying students with low motivation (Cocea and Weibelzahl, 2006), 5) determining if a student will complete an assignment (Drăgulescu et al., 2015), and 6) assessing students' interaction with the learning materials (Cobo et al., 2014; McCuaig and Baldwin, 2012; Paiva et al., 2016). Most of these previous studies have emphasized on how the success or failure of learners in a learning situation could be predicted using information regarding their interactions with the course materials. The review also showed that classification was mostly used to determine certain behavioral patterns in LMS (Scheffel et al., 2011) based on the usage patterns gathered from student activities (Paiva et al., 2016).

In addition, classification was also used to improve the efficiency and effectiveness of the learning processes (Beikzadeh and Delavari, 2005) and to provide some guidelines for the higher education system, thus improving the overall decision-making process. Based on these, it can be said that the use of classification would allow more flexibility for decision-makers to evaluate the performance and behavior of a group of students in order to determine how individual members of the group are likely to perform well in a learning task even if their specific knowledge or abilities does not fit to the task. Therefore, this technique can be effectively used to provide students with early interventions in the form of academic support, particularly to motivate students who are expected to not perform well in specific activity or class and to measure the positive and negative reactions, accurately, that form the efficiency of the classification model.

5.2. Clustering

Clustering is an identification or grouping of similar classes of objects. It aims at screening large datasets in order to establish useful inferences in the form of new relationships, patterns, or clusters, for decision-making (Romero and Ventura, 2007). The use of clustering in higher education is mainly to support students' interaction in different learning situations (Siemens and Long, 2011), recommend activities and resources to similar users, find groups of students with similar learning characteristics based on the content of visited pages and their traversal path patterns (skills and knowledge) (Ayers et al., 2009; Hϕmϕlϕinen et al., 2004; Tang and McCalla, 2002), examine students' achievement and involvement in the learning process (Cerezo et al., 2016). Such activities could help educational decision makers to identify potential dropouts at the early stage and to solve the problem of allocating new students to courses that are not of their interest (Cerezo et al., 2016; Kardan and Conati, 2010; Ratnapala et al., 2014; Zukhri and Omar, 2008).

In addition, clustering could enable educators to predict the student's learning outcome from LMS logs, identify undesirable student behaviors (Romero and Ventura, 2010), and support instructors in the collaborative student modeling process by monitoring the collective interaction among students in order to evaluate their performance (Hernándeza et al., 2006). This technique has also been used to support students' acquisition of various scientific skills (Salas et al., 2016), discover common learning routes in Moodle (Bogarin Vega et al., 2016), and understand the collaborative inquiry process among individual students (Anjewierden et al., 2007). In conclusion, it can be said that clustering in higher education might still be considered as an effective technique to group students based on their learning characteristics, individual learning style preferences, academic performance, and behavioral interaction. It can also be used to explore collaborative learning patterns and to boost the retention rate that would allow institutions to identify at-risk students at an early stage.

5.3. Visual data mining

Visual data mining combines traditional data mining methods with data visualization tools in order to visualize patterns of interest (Müller and Schumann, 2002). It is commonly used for exploratory data analysis. In higher education, visual data mining is used to graphically reduce complex and multidimensional student tracking data collected from web-based educational systems, which would help instructors to effectively analyze the different aspects of the learning process (Romero and Ventura, 2007). Several studies (Jin et al., 2009; Peña-Ayala, 2014; Yoo et al., 2006) have used visual mining techniques to facilitate the monitoring of students' learning activities as well as evaluate their behavior, participation, and performance during their interaction with the learning system. Visual data mining has also been applied in higher education to help instructors (involved in online learning) understand how their students work and navigate in a LMS environment, and discover students' behavior and engagement during the learning activity (García-Saiz and Zorrilla, 2010; Johnson and Barnes, 2010). Moreover, visual data mining can assist instructors to obtain further feedback about students' learning in order to evaluate the complexity of the learning task and supplied materials (Jovanović et al., 2007; Zaiane, 2001). Macfadyen and Sorenson (2010) applied visual data mining to map learners' online engagement with the course materials. It can also be used to visualize social aspects in CSCL, and conversations within online groups. Our review of the literature showed that instructors can manipulate the graphical representations of students' activities which allow them to get a better understanding of what is happening in the distance classes (Romero and Ventura, 2007). Based on these observations, it can be anticipated that visual data mining techniques can be used to present different educational data using graphs which may allow instructors and educational decision-makers to explore and gain insights into students' performance, so that appropriate support can be provided.

5.4. Statistics

Statistics is a mathematical method that focuses on the collection, analysis, interpretation, and presentation of data by using statistical software (Heathcote and Dawson, 2005). It can be used to evaluate relevant learning behaviors essential for guiding the development of learning strategies based on the patterns of use (consisting of the frequency of visits, access to learning materials, and participation in discussion forums), and to help instructors understand how to use web server logs information for formative evaluation (Ingram, 1999; Wu and Leung, 2002). Instructors may use these techniques to understand the association between students' participation in online activities and their learning outcomes (Chamizo-Gonzalez et al., 2015).

In the literature (see Table II in Appendix), the use of statistical techniques in higher education have been widely associated with the prediction of 1) student success (Simpson, 2006), 2) self-regulated learning and online course achievement (You, 2016), 3) student motivation (Lonn et al., 2015), 4) students' retention in college (DeBerard et al., 2004), and 5) students' graduation rates. Outcomes from these measures are likely to provide new knowledge for decision makers that could be used to solve diverse learning problems. This is believed to help instructors and course designers to gain general insights into students' behavior in a learning process.

5.5. Association rule

Association rule is a mining technique used to discover relationships between variables and attribute groups for a certain input pattern. It is used to discover learning rules (Minaei-Bidgoli and Tan, 2004; Ventura et al., 2008) based on students' characteristics and competencies (Romero et al., 2013) in order to make the courseware more effective (Retalis et al., 2006; Shen et al., 2003). This is because it enables instructors to analyze students' learning patterns and organize the course material more efficiently. In addition, it can be used for promoting collaborative learning (Yu et al., 2001), providing feedback to support instructors' decisions (Romero et al., 2004), identifying unusual learning patterns (Wang, 2002), predicting student's performance (final grades) based on features extracted from logged data in an e-learning environment (Nebot et al., 2006; Shangping and Ping, 2008; Zafra and Ventura, 2009), monitoring and evaluation of academic performance (tests and examination scores) (Ogor, 2007), and recommending learning materials based on learners' access history (Markellou et al., 2005). Our review showed that using such techniques may help in constructing concept maps that would enable instructors to overcome certain learning barriers and misconceptions of learners (Lee et al., 2009; Tseng et al., 2007).

The association rule technique has also been used for planning strategies to understand whether curriculum revisions can affect students' learning in different settings (Becker et al., 2000), and make decisions on how to improve the quality of the LMS services provided by the university based on the students' success and failure rates (Selmoune and Alimazighi, 2008). Previous studies have also reported the potential of this tool in identifying regular knowledge and associations between attributes in a large dataset such as web-based educational systems: where traditional statistical analysis may not provide enough insights into the creation of the corresponding rules. Therefore, association rules are used to identify relationships between students' behaviors, learning materials, and characteristics of performance disparity.

5.6. Regression

Regression is a prediction technique used to determine the relationships between dependent variables (target field) and one or more independent variables, as well as determining how such relationships can contribute to individuals' learning outcomes. Previous studies on e-learning analytics have shown the role of this technique in fitting students to a specific task complexity based on the association between one or more parameters. Some of the common uses of regression in higher education include prediction of students' performance (Golding and Donaldson, 2006; Tovar and Soto, 2010), behavior (Jo et al., 2017; Myller et al., 2002), knowledge (Pedro et al., 2013; Yudelson et al., 2010), and score or grades (Nasiri and Minaei, 2012; Pardos et al., 2012; Sweeney et al., 2015; Trivedi et al., 2010). In addition, instructors can use this technique to suggest effective strategies essential to enforce students' active participation in the learning process (Sabourin et al., 2012), exploiting learner models for e-learning with regard to the students' level of competencies (Holzhüter et al., 2013). It can be also used to investigate how university students' characteristics and experiences affect their satisfaction with LMS as an attempt to avoid students' dropout from the course (Thomas and Galambos, 2004).

The regression technique can also help predict success in colleges' courses (Martinez, 2001) by building linear regression models to identify factors essential for improving teaching and course quality (Jiang et al., 2016). Based on these studies, it can be concluded that regression can be effectively used for prediction purposes just like the classification techniques. However, in a classification, the predictor is the categorical task while in regression it is a numerical value or continuous task. For this reason, EDM researchers often apply several regression techniques for predicting students' academic performance and identifying variables that could predict the success or failure in university courses.

5.7. Sequential pattern

Sequential pattern is a mining technique used to discover the relationships between occurrences of sequential events, mainly to discover any specific order in the occurrences of these events (Romero and Ventura, 2010). In higher education, this technique has been applied to personalize recommendations for web-based learning systems based on the learning style preferences of students (Zhang et al., 2008) and to efficiently acquire knowledge essential to construct student models (Antunes, 2008). In collaborative learning, it can be used to discover which information sequence can be used to predict high achievers from low achieving groups (Maldonado et al., 2010; Nakamura et al., 2015). This include predicating students' intermediate mental steps in a sequence of actions that can be performed within a problem solving setting (Nesbit et al., 2008; Robinet et al., 2007). Therefore, it can be anticipated that the sequential pattern technique can be used to summarize the students' historical learning patterns (logs) in order to identify potential sequential patterns of learning by filtering items or events according to the common learning sequences. It can be also used to find hidden patterns to improve the quality of recommendations and solve relevant educational problems. While casual data mining technique focuses on finding the cause of certain events, a causal relationship can be inferred, if an educational event is randomly chosen using automated experimentation, which can ultimately lead to a positive learning outcome.

5.8. Text mining

Text mining is a technique used to find interesting patterns from large databases. It refers to the process of extracting information and knowledge from unstructured text (Gupta and Lehal, 2009). This technique has been successfully applied in different types of web-based educational system, mostly in collaborative learning (Ueno, 2004), to provide automatic formative assessment (Hsu et al., 2011) that is usually carried out in discussion forums. Text mining could improve instructors' ability to assess the progress of the group discussion (Dringus and Ellis, 2005), facilitate the process of building concept maps based on the messages posted to an online discussion board (Huang et al., 2006; Lau et al., 2007), gain a deeper understanding of online participation and achievement from a large amount of online learning data (He, 2013), and explore if there are any differences in students' cognitive learning outcomes, particularly for those with different learning backgrounds (Huang et al., 2006). Based on these observations, it is anticipated that educational policy makers may apply text mining to examine contents from online discussion forums, emails or chats which can yield considerable insights and expose valuable patterns in students' learning behaviors.

5.9. Correlation

A correlation mining is a measure of the linear relationship between two variables (Rayward-Smith, 2007). In the education sector, it can be used to predict students' performance based on their final exam score and interactions in an online homework tutoring (Pritchard and Warnakulasooriya, 2005), predict student success in a university (Mcdonald, 2004), identify the key formative assessment rules according to the web-based learning portfolios of an individual learner and to support mobile formative assessment which may help instructors better understand the main factors influencing student performance (Chen and Chen, 2009), conceptualize formative assessment as an ongoing process of monitoring the learners' progresses of knowledge construction (Hsu et al., 2011), and create concept models that offer a more plausible picture of the student knowledge (Barnes, 2005; Lee, 2007; Rai et al., 2009). Our review also showed that correlation has the potential to examine the psychometric properties of student data (France et al., 2010; Hsu et al., 2011). These insights may help instructors understand the main factors influencing student's performance. In addition, correlation mining can be effectively used to match between the students' knowledge and the course offered to them at a particular time period, so that students can learn based on their specific learning abilities and skills.

5.10. Outlier detection

Outlier detection is a technique used to discover learning events or effective practices from a large dataset (Romero and Ventura, 2013). They can be novel, new, abnormal behavior, unusual, or noisy reactions (Bakar et al., 2006). In the higher education sector, only a few studies had considered this technique in processing large datasets in which the focus was to analyze students' learning problems, identify deviations in the learner's or instructor's behavior or actions, and identify irregular learning processes (Castro et al., 2005; Suganya and Narayani, 2017; Ueno, 2004). In addition, outlier detection can be useful for detecting and removing irregular observations from an educational dataset, as well as identifying errors in learning systems.

Our review of the literature showed that both EDM and LA are useful analytical tools that would enable higher education to discover hidden patterns in educational databases, particularly to build models to accurately predict students' behavior, monitor students' performance constantly, allocate appropriate learning resources, address issues related to dropout and retention, and improve the effectiveness of learning systems. Table 3 presents the utilization of data mining techniques across the four dimensions. The analytical data are not restricted to students' interactions with an educational system, but may also be associated with students' collaboration, instructors' feedback, and evaluation of learning materials.

As shown in Table 3, some EDM and LA techniques were used more often than others, regardless of the learning activity. The choice of which technique to use or apply depends largely on the type of problem to be resolved. For example, many research works have been pursuing the development of EDM applications to predict, monitor, and evaluate student performance using techniques such as classification, clustering, regression, association rule mining, visual data mining, and text mining. The main measures used by these techniques were mostly related to students' level of achievement or success in a course (Bhardwaj and Pal, 2012; Kaur and Singh, 2016; McCuaig and Baldwin, 2012; Pradeep et al., 2015; Shaleena and Paul, 2015), final grades or score (Pardos et al., 2012; Rajeswari and Lawrance, 2016; Trivedi et al., 2010), knowledge (Kovanović et al., 2015; Parack et al., 2012; Vasić et al., 2015), participation (Janssen et al., 2007; Lopez et al., 2012; Romero et al., 2013; Xing et al., 2015), engagement (Cruz-Benito et al., 2015; Macfadyen and Sorenson, 2010; Pardo et al., 2017; Silva et al., 2016; Stanca and Felea, 2016), acquisition (Andrejko et al., 2007; Salas et al., 2016), metacognition (Agustianto et al., 2016; Aleven et al., 2006; Conati and Vanlehn, 2000; Molina et al., 2012; Winne and Baker, 2013; Wolpers et al., 2007), and the time a student spent on the learning task (Xiong and Pardos, 2011).

There were also studies that have applied other techniques such as sequential pattern mining, correlation mining, causal data mining, and outlier detection for similar purposes. Many studies have also been dedicated to regulate the complexity of the representation (Drăgulescu et al., 2015; Holzhüter et al., 2013; Pejić and Molcer, 2016) and provide pedagogical support to students (Cambruzzi et al., 2015; Little et al., 2011; Mazza and Dimitrova, 2004; Pardo et al., 2016) using techniques such as classification, clustering, association rule mining, and visual data mining. Techniques such as classification, clustering, association rule mining, text mining, visual data mining, and statistics have been frequently used to analyze student learning and interaction in different collaborative activities (Cobo et al., 2014; Ji et al., 2016; McCuaig and Baldwin, 2012; Paiva et al., 2016), as well as providing learning opportunities that incorporate student prior knowledge of content (Agustianto et al., 2016; Aher and Lobo, 2013; Chen et al., 2008; Chrysostomou et al., 2009; Macfadyen and Dawson, 2010). Other techniques, such as classification, clustering, association rule

Table 3
Utilization of data mining techniques across dimensions.

Dimensions/Techniques	Classification	Regression	Density estimation	Clustering	Association rule mining	sequential pattern mining	Correlation mining	Causal data mining	Outlier detection	Text mining	Visual data mining	Statistics
COMPUTER-SUPPORTED LEARNING ANALYTICS												
Collaborative learning												
Interaction	X			X	X	X				X	X	X
Social Network Analysis						X						
Student Actors	X			X								X
Collaborative task	X			X			X			X	X	X
Students preferences	X	X		X		X	X					X
Communication	X									X	X	X
Recommendations	X			X	X	X						X
Modeling cooperative relations				X		X					X	
Discovering patterns of academic collaboration	X				X	X				X	X	X
Self-learning behavior/self-assessment/self-regulated Learning												
Problem-solving activity	X	X		X	X	X			X		X	X
Students' self-assessment	X				X				X	X	X	X
COMPUTER-SUPPORTED PREDICTIVE ANALYTICS												
Learning material evaluation (course, content, and task)												
Task complexity evaluation	X	X		X	X							
Pedagogical support	X			X	X					X	X	
Feedback-supported learning decision	X			X	X		X			X	X	X
Planning strategies	X			X	X	X					X	
Evaluate learning materials	X	X	X	X	X					X	X	X
Students' learning performance/assessment/monitoring/others												
Achievement/success	X	X		X	X	X	X	X	X		X	X
Efficiency/Effectiveness	X	X		X							X	X
Elapsed time	X	X										
Competency				X								X
Correctness	X	X		X			X					X
Domain knowledge	X	X		X	X			X		X	X	X
Grades	X	X		X	X		X				X	X
Deficiencies	X	X			X						X	
Participation	X	X								X	X	X
Engagement	X	X		X							X	X
Reflection	X					X				X	X	X
Skills	X	X			X						X	X
Acquisition	X	X		X	X	X					X	
Inquiry	X			X						X		
Meta-cognitive	X			X		X					X	
Others	X	X		X	X		X		X	X	X	X
Dropout and retention												
Motivation	X			X	X							X
Satisfaction	X	X		X								X
Reflection and awareness	X			X							X	X
Others	X											X

(*continued on next page*)

Table 3 (*continued*)

Dimensions/Techniques	Classification	Regression	Density estimation	Clustering	Association rule mining	sequential pattern mining	Correlation mining	Causal data mining	Outlier detection	Text mining	Visual data mining	Statistics
COMPUTER-SUPPORTED BEHAVIORAL ANALYTICS												
Actions modelling	X	X		X	X	X	X	X	X		X	X
Pattern modelling	X	X		X	X	X	X		X		X	X
Knowledge modelling	X	X		X	X	X	X	X	X			X
COMPUTER-SUPPORTED VISUALIZATION ANALYTICS												
Mapping, text-based cloud, networks, charts and graphs	X		X	X	X		X	X		X	X	X

mining, regression, sequential pattern mining, correlation mining, causal data mining, outlier detection, visual data mining, and statistics, have been widely used in modeling or mining learner behavior in certain conditions (Castro et al., 2005; Cerezo et al., 2016; Mankad, 2016; Nesbit et al., 2008; Paiva et al., 2016). Many of these techniques were commonly used to identify and detect patterns of academic collaboration or unusual behaviors in different learning activities (see Table II in the appendix for more details). The outcomes from these processes can enable the learning system to take the necessary measures and actions in a timely manner.

6. Discussion

The knowledge discovered by different data mining techniques could enable the higher learning institutions to make better decisions, provide more advanced planning in directing students, predicting future trends and individual behaviors with higher accuracy, and enabling the institution to allocate resources and staff more effectively. Our review of the literature revealed that the use of both EDM and LA can play an important role to improve students' learning experience and learning outcomes, and to discover patterns and make predictions of students' behaviors and achievements, domain knowledge content, performance and assessments (Chamizo-Gonzalez et al., 2015; Peña-Ayala, 2014; Cristobal Romero and Ventura, 2007; Romero and Ventura, 2010).

The applications of EDM/LA are a growing phenomenon of the 21st century higher education. In this review, we classified previous works into four main dimensions labeled as: CSLA, CSPA, CSBA, and CSVA (Table 3 presents the major techniques discussed above and its relations to the four dimensions). In general, the first observation that can be made is that most of the surveyed papers focused on solving problems related to CSPA (63%), specifically deals with predicting student's performance where there is a huge collection of studies on this topic in educational journals and conferences, followed by CSLA (30%). These results are in line with the previous review conducted by Romero and Ventura (2010), which confirmed the potential of using classification and regression techniques in the prediction of students' progression in the task. Our review found that there were few studies on CSBA (20%), which are mainly used to aid students' problem-solving skills. This result is not in agreement to that of Peña-Ayala (2014) (reviewed EDM/LA between 2010 and 2013), which reported that CSBA to be one of the most preferred application of EDM for the purpose of describing or predicting certain behavior patterns, followed by CSPA. A possible reason to this is the recent recognition of the importance of CSPA in solving more challenging problems of nowadays technology. Although CSVA is often seen as one of the most important technique, it recorded the lowest number of the surveyed papers in this review (10%). This finding is similar to that reported in previous reviews (Peña-Ayala, 2014; Romero and Ventura, 2010).

In general, it was found in this review, the most frequently techniques used in the surveyed works were classification (26%), followed by clustering (21%), visual data mining (15%), statistics (14%), association rule mining (14%), and regression (10%). This conclusion is in agreement with Papamitsiou and Economides (2014) who reported a high frequency of studies that involved the use of the classification technique to solve specific learning problems, followed by clustering and regression. Yet, our results are inconsistent with the review of EDM use in Cristobal Romero and Ventura (2007) which reported that association rule mining (43%) is able to provide more opportunities compared to classification (28%) and clustering (15%).

Previous studies have mainly used specific techniques for solving certain identified learning problems. Our review of the literature showed that the commonly used techniques for solving CSLA problems were classification (accounted for 19% of the total number of research), statistics (17%), clustering (16%), and visual data mining (16%). This can be reasoned to the potential of using these four techniques in providing appropriate solutions for exploring patterns related to students' experiences in different learning situations. As shown in Table II in the appendix, most of previous studies used these techniques to solve problems related to students' collaboration and problem-solving activities, student preferences, recommendations, and students' self-assessment.

As for CSPA, it was found that different data mining techniques were commonly used to evaluate online learning materials (such as course, content, and task), and students' learning activities (such as learning performance, assessment, monitoring, and participation). In addition, monitoring individual student performance or success based on their final grades, and participation in online courses were the most concepts in which researchers have mainly used EDM and LA methods (see Table II in the Appendix). The review results showed that classification was the most frequently used technique for solving CSPA problems (30%), followed by clustering (15%). This can be attributed to that classification is an effective technique for predicting patterns of interest. Furthermore, both classification and prediction are used to form learning models for promoting certain learning tasks. While clustering technique can be broadly used to identify the object of similar classes by grouping students based on their interaction and patterns of learning difficulties (Siemens and Long, 2011), discover common learning routes in Moodle (Bogarin Vega et al., 2016), and detect undesirable student behaviors (Romero and Ventura, 2010). In addition, visualization and statistical techniques (12%) were also found to provide a general view of students' learning, highlight useful information, and to support the overall decision-making process (Romero and Ventura, 2010). On the contrary, outlier detection recorded the lowest level of importance with respect to CSPA.

With regards to CSBA, previous studies have been using EDM and LA to offer colleges and universities the ability to discover hidden patterns in large databases and to build models with high levels of accuracy. These models were found to provide an effective solution for designing online courses. Clustering (27%) was the most often technique used in solving learning problems related to CSBA due to its effectiveness in identifying hidden patterns related to students' learning styles and finding undesirable student behaviors (Parack et al., 2012). The classification technique was ranked the second most frequently used technique (18%), it was mostly used to construct and develop predictive model for students' performance, followed by the association rule mining (14%) and visualization (11%) respectively. Whilst correlation mining, causal data mining and outlier detection were the least used techniques in this dimension. We think that such limited use can be attributed to the complexity of these techniques in acquiring the necessary attributes for regulating or adapting certain users' needs to the task at hand.

As for CSVA, different types of techniques have been used to represent known/unknown concepts using concept maps, represent

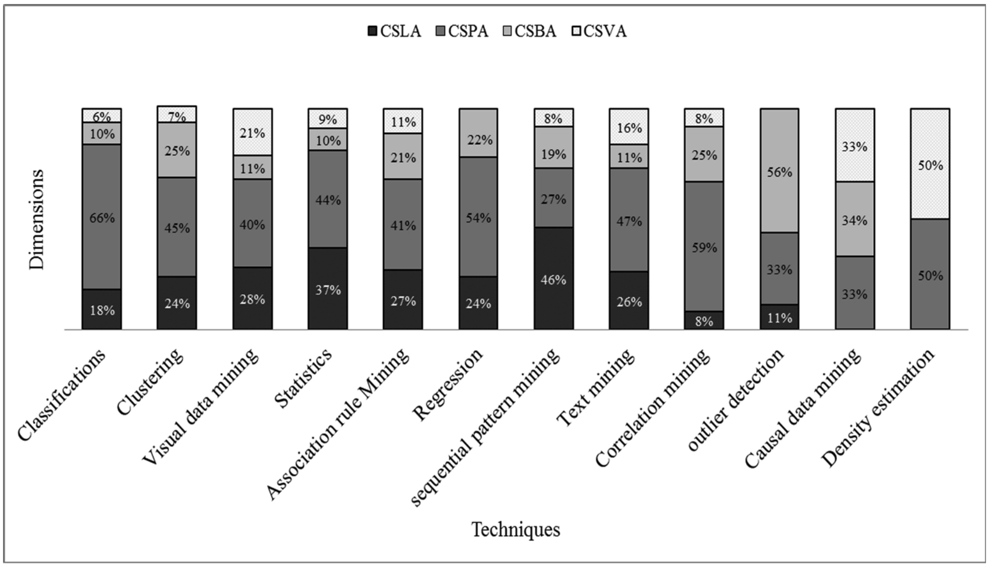
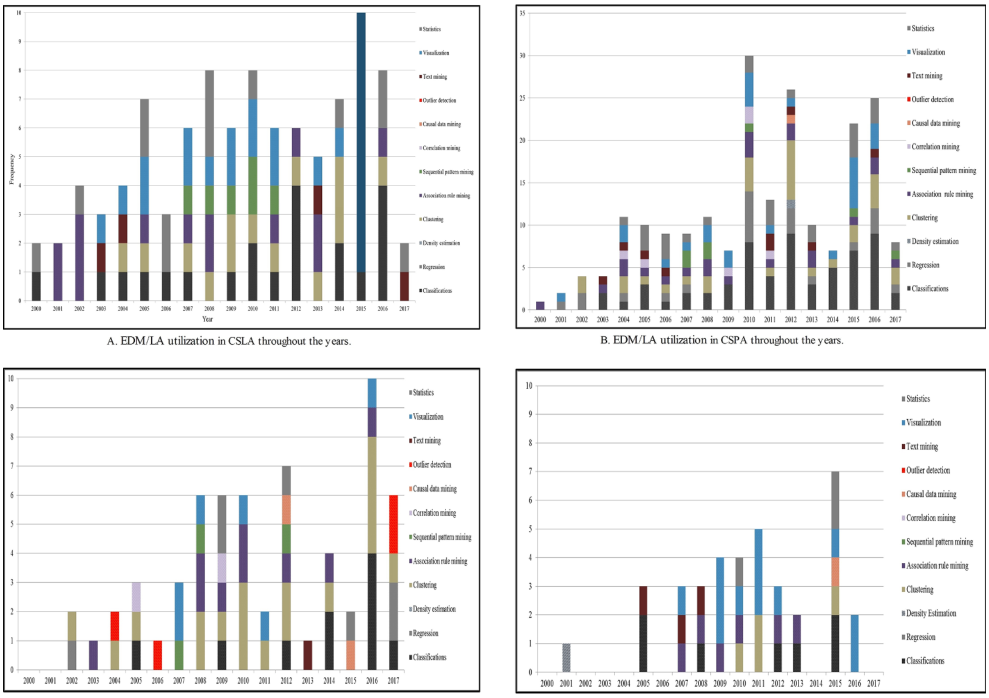


Fig. 4. The use of data mining techniques across the four dimensions.

levels of a student's knowledge as well as to help in solving data representation problems. The visual data mining technique was found to be the most widely used technique in this dimension (30%). This technique allows the disclosure of previously unknown and hidden information as well as patterns within the data. The presentation of the processed information using visualization techniques (Keim et al., 2010) can 1) offer a comprehensive view of the data, 2) graphically render complex student tracking data collected by LMS/CMS, and 3) identify interesting subsets (Mazza and Dimitrova, 2004). Outcomes from using visual data mining can enhance knowledge and improve decision-making processes in higher education institutions. These outcomes can reveal valuable information and hidden insights, associations, or relationships that can be used to facilitate a deeper understanding of students' interactions in different learning settings. This would enable decision-makers and system developers to effectively redesign learning opportunities and courses. For example, the visualization of information gained from the LMS can be directly used as a significant indicator of



A. EDM/LA utilization in CSLA throughout the years.

B. EDM/LA utilization in CSPA throughout the years.

C. EDM/LA utilization in CSBA throughout the years.

D. EDM/LA utilization in CSVA throughout the years.

Fig. 5. The development in the applications of EDM and LA throughout the years.

student dropout or noncompletion. Moreover, courses can be visualized to discover hidden relations and thus courses with overlapping contents can be identified via a transparent visualization that would enable instructors to redesign and improve the efficiency of course delivery (Vatrapu et al., 2011). The classification technique was widely used due to its effectiveness in providing useful information to experts for making reliable decisions. This was followed by association rule mining (15%) which was found to play an important role in discovering associations between student characteristics, learning problems, and strategies to improve the online experiences of students (Minaei-Bidgoli and Tan, 2004; Ventura et al., 2008). Although the statistical technique is supposed to be more relevant to this dimension (Romero and Ventura, 2007), it tends to be regarded as less important. Similarity, correlation mining and outlier detection were found to be the least data mining tools used in CSVA. Fig. 4 shows the usage ratio of each technique to solve a specific learning problem across the four dimensions.

Most techniques of data mining were used to embark on the continuous refinement and evaluation of learners' outcomes. As a result, valuable information and hidden insights or associations were revealed. Fig. 5 shows the utilization of EDM and LA in higher education throughout the years 2000 and 2017 (for more details see Fig. I in the Appendix). The utilization of EDM and LA in the four dimensions has rapidly increased in response to the current technological trends. This can be attributed to the increase complexity of technology and the varied channels and means for learning and teaching in online environments.

Many specific empirical studies have been carried out, and dimensions such as CSPA and CSLA have been studied to a great depth. In addition, the focus has been extended to the applications of CSBA and CSVA, as shown in Fig. 5, particularly for predicting an individual's behavior in the learning environment. Our review showed that the number of studies on EDM and LA during the period between 2000 and 2005 was minimal and limited to the use of statistics and regression techniques. The number of research has progressively increased over the last five years, largely as a result of an increase in the number of online learning classrooms, especially with the development of massive open online courses. From 2006 onwards, techniques such as correlation mining, causal data mining, and outlier detection have been applied to the education sector and researchers used them along with other techniques to provide more effective solutions and recommendations.

In summary, research on CSPA has always been on the rise, and it is expected to continue holding the greatest promise for the future of higher education. Similarity, CSLA has also received, to some extent, the attention of researchers over the last three years. It is also important to note that the applications of CSVA are still under-researched in education.

7. Conclusion

In this paper we survey 402 articles describing applications of EDM and LA in higher education. We found that EDM and LA are commonly used to provide opportunities and solutions to various learning problems related to CSLA, CSPA, CABA, and CSVA. In general, most data mining techniques are well suited for specialization of EDM and LA. The major data mining techniques of clustering, association rule, visual data mining, statistics, and regression are commonly used across these dimensions. However, this review has found that some techniques, such as sequential pattern mining, text mining, correlation mining, outlier detection, causal mining, and density estimation, are not commonly used due to the complexity in obtaining the attributes necessary to regulate or adapt to individual needs. Furthermore, we find that CSPA sees a higher rate of classification tasks due as classification has been accepted as an effective technique for predicting patterns of interest to form learning models for promoting specific learning tasks. Correspondingly we did not find any practical real-world uses of regression for the dimensions of CSVA. In summary, we find that the application of EDM/LA can provide significant benefits, and therefore urge higher education institutions to adopt them where feasible. Our survey can aid them in selecting the right technique for the right use case. Further, the application of EDM and LA in higher education may help in developing more student-focused provision, and provide data and tools that institutions will be able to use for real-time prediction.

Conflict of interest

The authors declare that they have no conflict of interest.

Acknowledgment

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Appendix

Table I
Search terms.

Database	Keywords	Combinations
Web of Science Science Direct IEEE Xplore Springer Link Scopus ERIC Google Scholar DBLP ACM Digital Library	Educational Data mining (Papamitsiou and Economides, 2014; Romero and Ventura, 2007; Romero and Ventura, 2010)	Educational data mining Techniques OR Methods Application of educational data mining AND [in higher education OR education OR educational sector] Educational data Mining Techniques OR Methods and their applications AND [in higher education OR education OR educational sector OR university context OR LMS OR CMS] Prediction OR Prediction Technique OR Methods AND [in higher education OR education OR educational sector] Classification OR Classification technique OR Classification Method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Clustering Techniques OR Method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Association rule mining AND [in higher education OR education OR educational sector] Sequential mining technique OR method AND [in higher education OR education OR educational sector] Causal data mining technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Association techniques OR methods AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Regression technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Text Mining technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Outlier Detection technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Density estimation technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS]
	Data mining (Baker, 2010; Han, Pei, and Kamber, 2011; Romero and Ventura, 2013; Romero et al. et al., 2008; Romero et al., 2008)	Data mining techniques OR Data Mining Methods AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Data mining application AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Classification technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Data Mining Techniques OR Methods and their applications AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Clustering technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Association rule mining technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Sequential mining technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Causal data mining technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Regression technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Text Mining technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Outlier Detection technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Density estimation technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS]
	Learning analytics (Ali et al., 2013; Papamitsiou and Economides, 2014; Romero and Ventura, 2013; Siemens and Long, 2011; Verbert et al., 2013)	Learning analytics Learning analytics application AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Learning analytics AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Data analytics AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Data analytics Application AND [in higher education OR education OR educational sector] Big data analytics AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS]
	Knowledge discovery (Alfonseca et al., 2007; Fayyad et al., 2002; Romero and Ventura, 2013; Romero et al., 2004)	Knowledge discovery AND [in education OR higher education OR educational sector] Knowledge discovery Application AND [in education OR higher education OR educational sector] Knowledge discovery techniques AND [in education OR higher education OR

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Table I (*continued*)

Database	Keywords	Combinations
		educational sector OR university context OR LMS OR CMS] Knowledge discovery techniques AND Application AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS]
	Machine learning (Hall et al., 2011; Huebner, 2013; Witten et al., 2016)	Machine learning techniques OR Method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Application of machine learning techniques OR method AND [in higher education OR education OR educational sector] Machine learning techniques AND application AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS]
	Artificial intelligence (Bhattacharyya and Hazarika, 2006; Huebner, 2013; Peña-Ayala, 2014)	Artificial intelligence AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS]
	Neural network (Castro et al., 2007; Romero et al., 2008; Singh and Chauhan, 2009)	Neural network AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS]
	Soft computing (Mitra and Acharya, 2003; C. b. Romero, Ventura, Pechenizkiy, and Baker, 2010; Yao, 2006)	Soft computing AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS]
	Data visualization (Fayyad, Wierse, and Grinstein, 2002; Keim, 2002)	Visual data mining technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Visualization technique OR method AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS] Visualization tools AND [in education OR higher education OR educational sector OR university context OR LMS OR CMS]

Table II
Utilization of data mining techniques across dimensions.

Objectives	Classification	Regression	Density estimation	Clustering	Association rule Mining	Sequential pattern mining	Correlation mining	Causal data mining	Outlier detection	Text mining	Visualization	Statistics
Computer-supported learning analytics												
Collaborative learning												
Interaction Online activities	(Agudo-Peregrina et al., 2014; Kim et al., 2012; Schrire, 2004; Macfadyen and Dawson, 2010; Paiva et al., 2016; Ji et al., 2016; Cobo et al., 2014; McCuaig and Baldwin, 2012; Cocea and Weibelzahl, 2006)			(Perera et al., 2009; Vasić et al., 2015;; Akçapýnar et al., 2014; Ratnapala et al., 2014; Talavera and Gaudioso, 2004)	(Lile, 2011; Yu et al., 2001; Wang, 2002)	(Kardan and Conati, 2010; Perera et al., 2009)				(He, 2013)	(Govaerts et al., 2010; Mostow et al., 2005; Scheffel et al., 2011; Ben-Zadok et al., 2009; Chamizo-Gonzalez et al., 2015; Ben-Naim et al., 2008)	(Chamizo-Gonzalez et al., 2015; Alves et al., 2015; Heathcote and Dawson, 2005)
Social Network Analysis												
- SStudent Actors	(Paiva et al., 2016)	(Finnegan et al., 2008)		(Ratnapala et al., 2014)								(Haythornthwaite, 2008)
- CCollaborative task	(Nankani et al., 2009)			(Xing et al., 2015)			(Rayward-Smith, 2007)			(Yim and Warschauer, 2017)	(Little et al., 2011; McKeon, 2009)	(Van Leeuwen et al., 2014)
- SStudents preferences				(Hung et al., 2016; Chen and Liou, 2014)			(Rai and Beck, 2010; Viola et al., 2006)					(Hung and Zhang, 2008)
CCommunication	(Anjewierden et al., 2007)									(Mochizuki et al., 2003)	(Janssen et al., 2007; Macfadyen and Dawson, 2010; Wolpers et al., 2007; Heathcote and Dawson, 2005)	(Haythornthwaite, 2008; Gruzd et al., 2016)
- RRecommendations	(Agustianto et al., 2016)			(Tang and McCalla, 2005; Aher and	(Aher and Lobo, 2013; Zaíane, 2002)	(Zhang et al., 2008)						(Macfadyen and Dawson, 2010; Chen et al., 2008)

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Table II (*continued*)

Objectives	Classification	Regression	Density estimation	Clustering	Association rule Mining	Sequential pattern mining	Correlation mining	Causal data mining	Outlier detection	Text mining	Visualization	Statistics
				Lobo, 2013; Chrysostomou et al., 2009)								
- MModeling cooperative relations				(Perera et al., 2009)		(Perera et al., 2009)				(Huang et al., 2007)	(McKeon, 2009)	
- DDiscovering patterns of academic collaboration	(Stanca and Felea, 2016)				(Kumar and Chadha, 2012)					(Ueno, 2004a; He and Yan, 2015; El-Halees, 2009; Zaiane, 2001)	(Janssen et al., 2007)	(Farzan and Brusilovsky, 2006)
Self-learning behavior/self-assessment/Self-Regulated Learning												
- Problem-solving activity	(Azevedo et al., 2010; Gobert et al., 2012; Pejić and Molcer, 2016; Sabourin et al., 2012; Conati and Vanlehn, 2000)	(Sabourin et al., 2012)		(Bouchet et al., 2012; Kerr and Chung, 2012; Maldonado et al., 2010; Hung et al., 2016)	(Tsai et al., 2016)	(Chi et al., 2011; Maldonado et al., 2010; Nesbit et al., 2007)			(Ueno, 2004b)		(Verbert et al., 2013)	(Nussbaumer et al., 2015; You, 2016; Pardo et al., 2017; Aleven et al., 2006)
- SStudents' self-assessment	(Conati and Vanlehn, 2000)								(Ueno and Nagaoka, 2002)	(Mochizuki et al., 2003; Ueno, 2004a)	(Mochizuki et al., 2003; de-la-Fuente-Valentín et al., 2015)	(Lin et al., 2015; Iglesias-Pradas et al., 2015)
Computer-supported predictive analytics												
Learning material evaluation (course, content, and task)												
- Task complexity evaluation	(Drăgulescu et al., 2015; Pejić and Molcer, 2016)	(Holzhüter et al., 2013)		(Bouchet et al., 2012)						(Grobelnik et al., 2002)		
- Pedagogical support	(Pardo et al., 2016)			(Tang and McCalla, 2002)	(Shi et al., 2012)						(Little et al., 2011; Mazza and Dimitrova, 2004;	

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Table II (*continued*)

Objectives	Classification	Regression	Density estimation	Clustering	Association rule Mining	Sequential pattern mining	Correlation mining	Causal data mining	Outlier detection	Text mining	Visualization	Statistics
											Cambruzzi et al., 2015)	
- Feedback-supported learning decision	(Gobert et al., 2012; Pechenizkiy et al., 2008)			(Scheffel et al., 2011; Aher and Lobo, 2013)	(Tsai et al., 2016; Romero et al., 2013a; Aher and Lobo, 2013;Cristóbal Romero et al., 2004)						(Wong and Li, 2016; Jovanović et al., 2007; Scheffel et al., 2011)	(Farzan and Brusilovsky, 2006; Markellou et al., 2005)
- Planning strategies	(Manek et al., 2016; Kerr and Chung, 2012; Mankad, 2016)			(Trivedi et al., 2012; Figueiredo et al., 2016)	(Onan et al., 2016; Becker et al., 2000; Selmoune and Alimazighi, 2008)	(Nakamura et al., 2015)					(Álvarez et al., 2016; Li et al., 2015)	
- Evaluate learning materials	(El-Halees, 2011; Vranic et al., 2007)	(Jiang et al., 2016)	(Sakurai et al., 2012)	(Bogarin Vega et al., 2016; Campagni et al., 2014)						(Hsu et al., 2011)		
Students' learning evaluation/Assessment/monitoring/ Performance/ Assessment/ others												
Achievement/success	(Beikzadeh and Delavari, 2005; Frey and Seitz, 2011; Pai et al., 2010; Martínez Abad et al., 2017; Kaur and Singh, 2016; Shaleena and Paul, 2015; Pradeep et al., 2015; McCuaig and Baldwin, 2012; Bhardwaj and Pal, 2012)	(Macfadyen and Dawson, 2010; Tang and McCalla, 2002; Tovar and Soto, 2010; Sabourin et al., 2012; Martinez, 2001; Golding and Donaldson, 2006)		(Maldonado et al., 2010; Sparks et al., 2012; Wu, 2010; Cerezo et al., 2016)	(Kumar and Chadha, 2012; Shi et al., 2012; Zhang, 2010; Ogor, 2007)	(Maldonado et al., 2010)	(Chen and Chen, 2009; Mcdonald, 2004)		(Patil and Kumar, 2017)		(Serrano-Laguna et al., 2012)	(Macfadyen and Dawson, 2010; DeBerard et al., 2004; You, 2016; Simpson, 2006)
- Efficiency/ Effectiveness	(Agudo-Peregrina et al., 2014;	(Elias and MacDonald, 2007)									(Li et al., 2015)	(Cen et al., 2007)

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Table II (*continued*)

Objectives	Classification	Regression	Density estimation	Clustering	Association rule Mining	Sequential pattern mining	Correlation mining	Causal data mining	Outlier detection	Text mining	Visualization	Statistics
	Zach A Pardos et al., 2014; Parmar et al., 2015)											
- Elapsed time	(Xiong and Pardos, 2011)											
- Competency		(Tovar and Soto, 2010)		(Salas et al., 2016)								(Iglesias-Pradas et al., 2015)
- Correctness	(Pechenizkiy et al., 2008)			(Pechenizkiy et al., 2008)								(Zheliazkova et al., 2015)
- Domain knowledge	(Pardos and Heffernan, 2010; Yudelson et al., 2010; Hussaan and Sehaba, 2014; Vasić et al., 2015)	(Yudelson, Pavlik et al., 2010; Pedro et al., 2013; Myller et al., 2002)		(Pardos et al., 2012; Gong et al., 2010; Kovanović et al., 2015; Myller et al., 2002)	(Hardof-Jaffe et al., 2010)		(Rai and Beck, 2010)	(Parack et al., 2012)		(Wong and Li, 2016)	(Mazza and Dimitrova, 2004; Chen et al., 2008)	(Jeong and Biswas, 2008)
- Grades	(Sun, 2010; Bunkar et al., 2012; Pardo et al., 2016; Rajeswari and Lawrance, 2016; Guleria et al., 2014; Cristobal Romero et al., 2013; Romero et al., 2008; Falakmasir and Habibi, 2010; Marbouti et al., 2016; Shovon and Haque, 2012; Ogor, 2007; Ahmed and Elaraby, 2014)	(Zachary Pardos et al., 2012; Nasiri and Minaei, 2012; Trivedi et al., 2010; Sweeney et al., 2015)		(Pardos et al., 2012; Brown et al., 2015; Shovon and Haque, 2012)	(Liu et al., 2010; Nebot et al., 2006; Shangping and Ping, 2008; Zafra and Ventura, 2009)		(France et al., 2010; Pritchard and Warnakulasooriya, 2005)				(Trivedi et al., 2010; de-la-Fuente-Valentín et al., 2015)	(Cristobal Romero et al., 2013; Chalaris et al., 2015; Macfadyen and Dawson, 2010)
- Deficiencies	(Falakmasir and Habibi, 2010)										(Yoo et al., 2006)	
- Participation	(Cristóbal Romero,	(Finnegan et al., 2008)								(Dringus and Ellis, 2005)		(Chamizo-Gonzalez et al.,

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Table II (*continued*)

Objectives	Classification	Regression	Density estimation	Clustering	Association rule Mining	Sequential pattern mining	Correlation mining	Causal data mining	Outlier detection	Text mining	Visualization	Statistics
	Manuel-Ignacio López et al., 2013; Xing et al., 2015; Sembiring et al., 2011; Lykourentzou et al., 2009)										(Chamizo-Gonzalez et al., 2015)	2015; Sembiring et al., 2011)
- Engagement	(Zach A Pardos et al., 2014; Pedro et al., 2013; Cocea and Weibelzahl, 2007)	(Silva et al., 2016; Stanca and Felea, 2016)		(Pardo et al., 2017)							(Macfadyen and Sorenson, 2010)	(Pardo et al., 2017)
- Reflection										(Mochizuki et al., 2003)	(Joshi et al., 2016)	(Joshi et al., 2016; Heathcote and Dawson, 2005)
- Skills	(Gobert et al., 2015)										(Chamizo-Gonzalez et al., 2015; Kordík and Kuznetsov, 2015)	(Chamizo-Gonzalez et al., 2015)
- Acquisition	(Casey and Azcona, 2017; Ogor, 2007)			(Salas et al., 2016)	(Kumar and Chadha, 2012)	(Antunes, 2008)					(Serrano-Laguna et al., 2012)	
- Inquiry	(Gobert et al., 2012; Gobert et al., 2015)			(Beikzadeh and Delavari, 2005; Sakurai et al., 2012; Tang and McCalla, 2002; Kovanović et al., 2015)						(Gobert et al., 2013)		
- Meta-Cognitive	(Azevedo et al., 2010; Schrire, 2004; Agustianto et al., 2016),			(Bouchet et al., 2012; Peckham and McCalla, 2012)		(Nesbit et al., 2007)				(Huang et al., 2006)	(de-la-Fuente-Valentín et al., 2015; Jeong and Biswas, 2008)	
- Others	(Delavari et al., 2005; Gobert et al., 2012; Xiong et al., 2010; Baradwaj and	(Gong and Beck, 2010; Koprinska, 2010)		(Wu, 2010; Kerr and Chung, 2012; Campagni et al., 2014)	(Beikzadeh and Delavari, 2005; Kumar and Chadha, 2012)		(Koprinska, 2010)		(Suganya and Narayani, 2017)	(Leong et al., 2012; Ueno, 2004a; Tane et al., 2004)	(Ben-Zadok et al., 2009; Ueno, 2004a)	(Ali et al., 2013)

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Table II (*continued*)

Objectives	Classification	Regression	Density estimation	Clustering	Association rule Mining	Sequential pattern mining	Correlation mining	Causal data mining	Outlier detection	Text mining	Visualization	Statistics
	Pal, 2012; Al-Radaideh et al., 2006)											
Dropout and retention												
- Motivation	(Pradeep et al., 2015)			(Rad et al., 2011)	(de Almeida Neto and Castro, 2015)							(Lonn et al., 2015)
- Satisfaction	(Dejaeger et al., 2012)	(Thomas and Galambos, 2004)		(Iam-On and Boongoen, 2017; Thomas and Galambos, 2004)								(Carter and Yeo, 2016)
- Reflection and awareness	(Yu et al., 2010; Márquez-Vera et al., 2016; Shaleena and Paul, 2015; Baradwaj and Pal, 2012)										(Govaerts et al., 2010; Mazza and Dimitrova, 2004; Cambruzzi et al., 2015; de-la-Fuente-Valentín et al., 2015)	(Lin, 2012)
- Others	(Morris et al., 2005; Bayer et al., 2012; Dekker et al., 2009)											(Morris et al., 2005)
Computer-supported behavioral analytics												
Modeling of learning behavior	(El-Halees, 2009; Zach A Pardos et al., 2014)			(El-Halees, 2009; Kardan and Conati, 2010; Parack et al., 2012; Tang and McCalla, 2002)	(El-Halees, 2009; Kardan and Conati, 2010; Cristóbal Romero et al., 2010)	(Shanabrook et al., 2010; Tang and McCalla, 2002)			(El-Halees, 2009)			
- Actions modeling	(Paiva et al., 2016; (Mankad, 2016; Cobo et al., 2014; McCuaig and Baldwin, 2012)			(Cerezo et al., 2016; Scheffel et al., 2011; Sisovic et al., 2016; Bogarin Vega et al., 2016; Ayesha et al., 2010; Talavera and Gaudioso,	(Hung and Zhang, 2008)	(Bouchet et al., 2012; Nesbit et al., 2007; Nesbit et al., 2008)		(Caputi and Garrido, 2015)	(Castro et al., 2005)		(Anjewierden et al., 2007; Scheffel et al., 2011),	(Cruz-Benito et al., 2015; Markellou et al., 2005)

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Table II (*continued*)

Objectives	Classification	Regression	Density estimation	Clustering	Association rule Mining	Sequential pattern mining	Correlation mining	Causal data mining	Outlier detection	Text mining	Visualization	Statistics
				2004; Cobo et al., 2010; Hung and Zhang, 2008)								
- Pattern modeling	(Beikzadeh and Delavari, 2005; Stanca and Felea, 2016; Casey and Azcona, 2017; Marbouti et al., 2016)	(Jo et al., 2017)		(Hung et al., 2016; Tang and McCalla, 2005; Parack et al., 2012; Peckham and McCalla, 2012)	(Parack et al., 2012; Tsai et al., 2016; Chen and Liou, 2014)	(Nesbit et al., 2007)	(Lee, 2007)	(Bakar et al., 2006)	(He, 2013)		(Wolpers et al., 2007; Álvarez et al., 2016; Wong and Li, 2016)	(Lin, 2012; Griffiths and Graham, 2009; Hung and Zhang, 2008)
- Knowledge modeling				(Iam-On and Boongoen, 2017)			(Barnes, 2005; Rai et al., 2009)	(Parack et al., 2012)				(Zheliazkova et al., 2015)
Computer-supported visualization analytics												
Decision modeling (Data-driven decision-making) - map-based, - ext-based cloud - networks, - charts and graphs	(Beikzadeh and Delavari, 2005; Dejaeger et al., 2012; Delavari et al., 2005; Cristobal Romero et al., 2013; Pradeep et al., 2015; Parmar et al., 2015)		(Zadrozny and Elkan, 2001)	(Scheffel et al., 2011; Rad et al., 2011;Wu, 2010; Cruz-Benito et al., 2015)	(Kumar and Chadha, 2012; Liu et al., 2010; Romero et al., 2013a; Tseng et al., 2007; Hwang, 2008; Lee et al., 2009)		(Barnes, 2005),	(Caputi and Garrido, 2015)		(Chen et al., 2008; Bari and Benzater, 2005)	(Little et al., 2011; McKeon, 2009; Scheffel et al., 2011; Serrano-Laguna et al., 2012; Chen et al., 2008; Paiva et al., 2016; Álvarez et al., 2016; Li et al., 2015; Sun, 2010; Jin et al., 2009; Nankani et al., 2009)	(Tovar and Soto, 2010; Lin et al., 2015; Lonn et al., 2015)

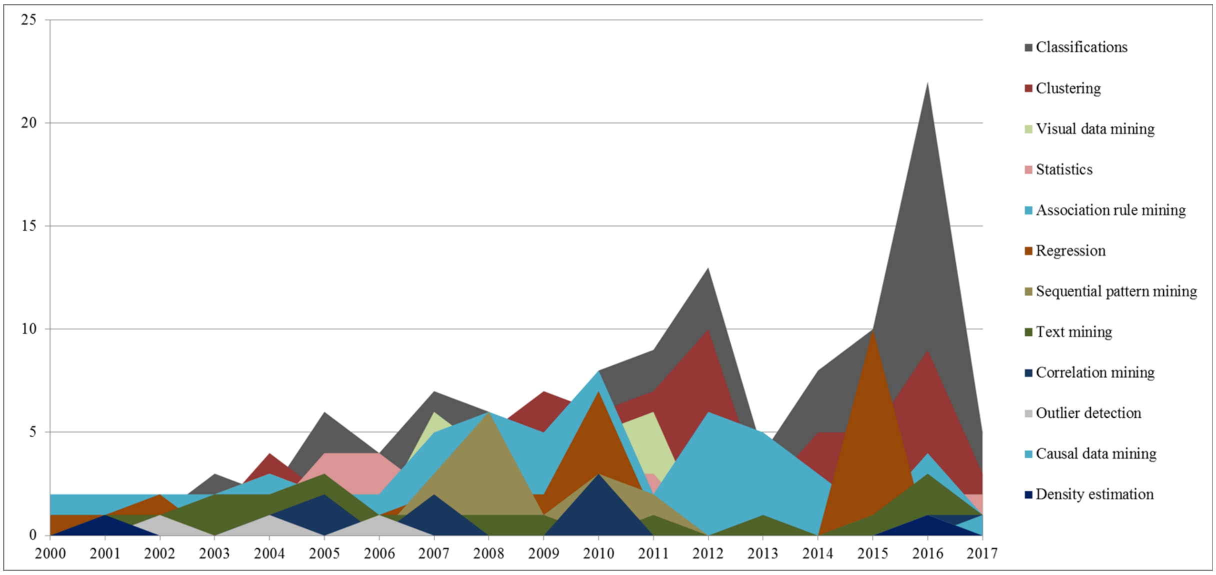

Fig. I. The development in the application of data mining techniques throughout the years.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tele.2019.01.007.

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