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The Role of Learning Analytics in Distance Learning: A SWOT Analysis

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ABSTRACT

The aim of this study was to analyze the role of learning analytics in education by discussing the phenomenon of learning analytics in detail. Thus, SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis was conducted in the study. Initially, a literature review was conducted and the role of learning analytics in the distance learning system was detailed with the analysis of available studies in the literature. Gathered studies were analyzed by the contexts of strengths, weaknesses, opputunities and threats of learning analytics on distance learning. The strengths are “flexible and innovative design”, “rising effectiveness”, “induvidualisation of learning or system” and “understanding user expectations”, and weaknesses are “determining parameters” and “lack of experts”. On the behalf of external factors, oppurtunities are “development in artifical intelligence”, “rom globalisation to localisation change trend” and “gathering big data easily”, and threats of learning analytics on distance learning are “ethical issues (security of data, accessing data, private information etc.)” and “information consumption”. Based on the SWOT matrix, it could be suggested that strengths and opportunities of learning analytics were more dominant when compared to its weaknesses and threats in distance learning.

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INTRODUCTION

Distance learning has become popular especially in the current situation since its introduction. In general, distance learning, which is described as time and space-independent learning activities, became an umbrella concept that covers learning approaches such as e-learning, mobile learning, and ubiquitous learning (Orhan Göksün, 2019: 17). It became one of the most adequate educational approaches in 21st century learning. Distance learning was introduced through mail and reduced to simple QR codes and made available for almost every individual. During these developments, distance learning and face to face education have been compared several times. These comparisons demonstrated that although it varief over time, the most important disadvantage of distance learning was the lack of interaction, inability to recognize the student since it is instructed to a larger audience; and thus, the lack of individualized education (Hurt, 2008).

One of the most crucial factors behind the prevalence of distance learning was the rapid diversification of knowledge and data. Especially after the development and popularization of computers and internet technologies, the data storage volume has increased significantly. About 300 exabytes (300 billion gigabytes) of new data are entered every day through computers. This led to the introduction of the “big data” concept. Big data refers to unstructured data pools without a significant pattern (Berman, 2013; Dean, 2014). These data pools could be defined based on three properties: volume, diversity, and velocity (Dean, 2014). The volume reflects the data saturation of the pool for the pattern of research, diversity reflects the width of the data range for the pattern of research in the data pool, and the velocity refers to cumulative changes in the data pool. Each data pool that could be described by one of these three parameters could be described as big data.

Due to the increase in online and offline data, the stored data became increasingly complex and standard data analysis techniques failed to cope with the big data, leading to the problem of how to utilize complex data mass (Berman, 2013). Thus, estimation and segmentation techniques came to the fore. Estimation techniques include logistic regression, neural networks, and decision trees, while segmentation techniques include clustering and classification analysis. While different techniques and analyzes could yield different results, the above-mentioned segmentation and estimation techniques provide interpretable findings (Pena-Ayala, 2014). These techniques were classified as descriptive and predictive techniques by Şimşek Gürsoy (2009; 2012).

Segmentation techniques are used to group the population or sample based on similar demographic, psychological or behavioral variables. Estimation techniques, on the other hand, are used in planning decisions and partially actions based on similarities of the groups. The findings obtained with these techniques and analyses have been used in the field of education in recent years along with data mining, educational data mining, learning analytics or academic analytics, as well as wide and effective use in the fields of finance, medicine, and advertising.

Data Mining

There are various definitions of data mining in the literature. Piateski and Frawley (1991) described data mining as the discovery of previously unknown and potentially useful data. Berry and Linoff (1997) described the concept as an exploratory and analytical process conducted on large data stacks to discover significant rules and patterns. In a study by Sever and Oğuz (2002), data mining was defined as a step in the process of the discovery of knowledge in databases, which allows to acquire previously unknown, hidden, significant and useful patterns in large database data. Based on these definitions, data mining could be described as the process of information, finding and pattern acquisition using big data.

Data mining is conducted in six main steps: goal definition, data understanding, data preparation, modeling, analysis and utilization (Bernstein, Provost & Hill, 2005; Pena-Ayala, 2014). A clearly defined data mining objective includes processes such as obtaining the required data from the databases, cleaning or analyzing the missing data, excluding noisy data, and comprehension and preparation of the data.

Patterns are developed using the acquired data using data mining models (descriptive/segmentation or estimator/prediction). These models are tested for the data set during the analysis phase for accuracy. In the final stage, the model is run with real data that was not included in the data set. Şimşek Gürsoy (2012) summarized the steps that should be employed in the data mining process and presented in Figure 1.

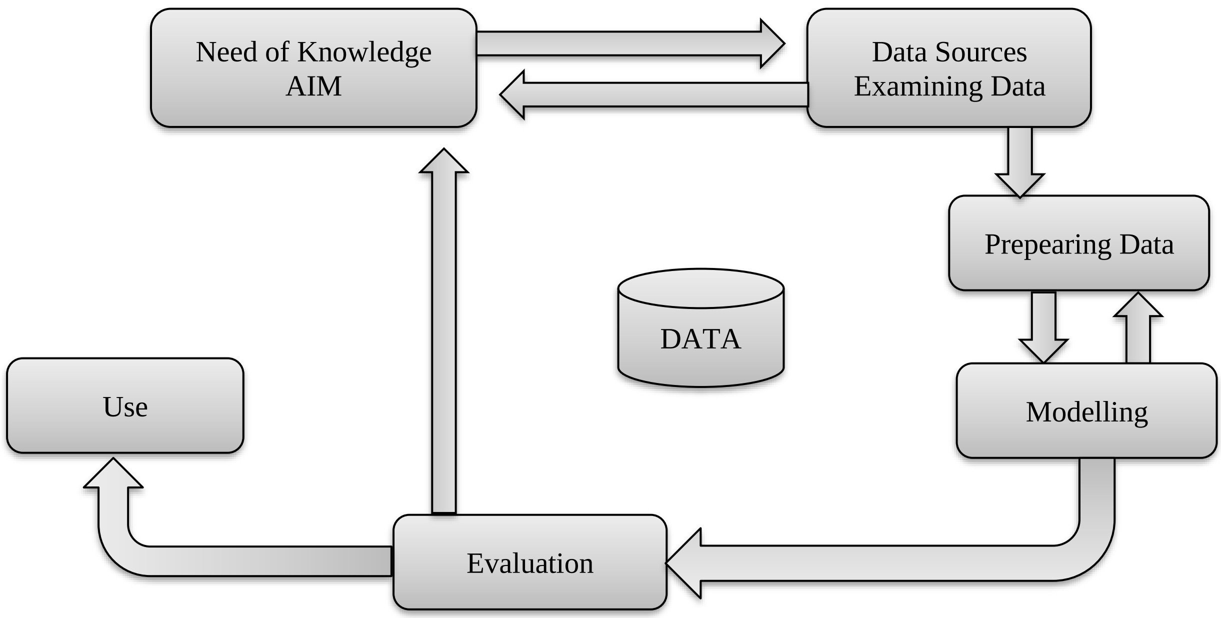

Figure 1. *Data Mining Analysis Process*

The review of Figure 1 demonstrated that data mining proposes a progress within the framework of the data by focusing on the data. Furthermore, although the discovery of information in databases was defined as a separate process from data mining in the literature (Karabatak, 2008; Şimşek Gürsoy, 2009), certain definitions suggested that these two concepts could be used interchangeably (Agrawal & Srikant, 1994; Şengür, 2013). Karabatak (2008) described the process of information discovery in databases as presented in Figure 2.

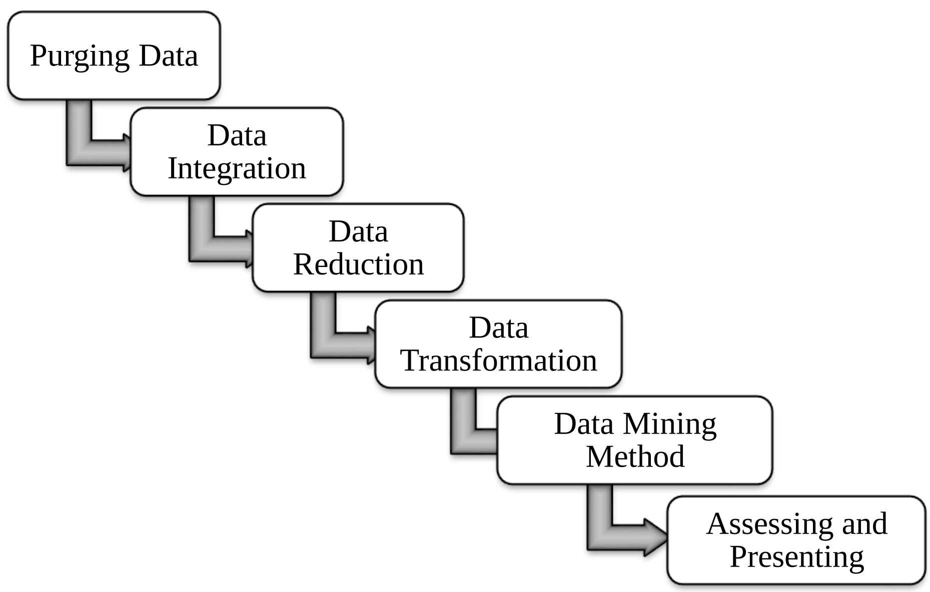

Figure 2. *Database Information Discovery Process*

As seen in Figure 2, the process of information discovery begins with data cleaning and ends with the analysis and presentation after the selection and implementation of the data mining method to transform the data into information. The comparison of the Figures 1 and 2 revealed that the data mining process includes the information discovery process, but it provides a more comprehensive roadmap that includes the stages of the determination of the objective and utilization of the information. Either way, the determination of the modeling/data mining method is a common step. Descriptive and predictive models are employed in data mining methods that tackle big data. In descriptive models, the aim is to define the patterns in available data to assist the decision-making process. The predictive models aim to develop a model based on the data with known outcomes and to calculate the results for the data sets with unknown outcomes (Şimşek Gürsoy, 2009). The above-mentioned models are divided into main and sub branches. The main and sub-branches and analysis methods employed in these models are presented in Figure 3.

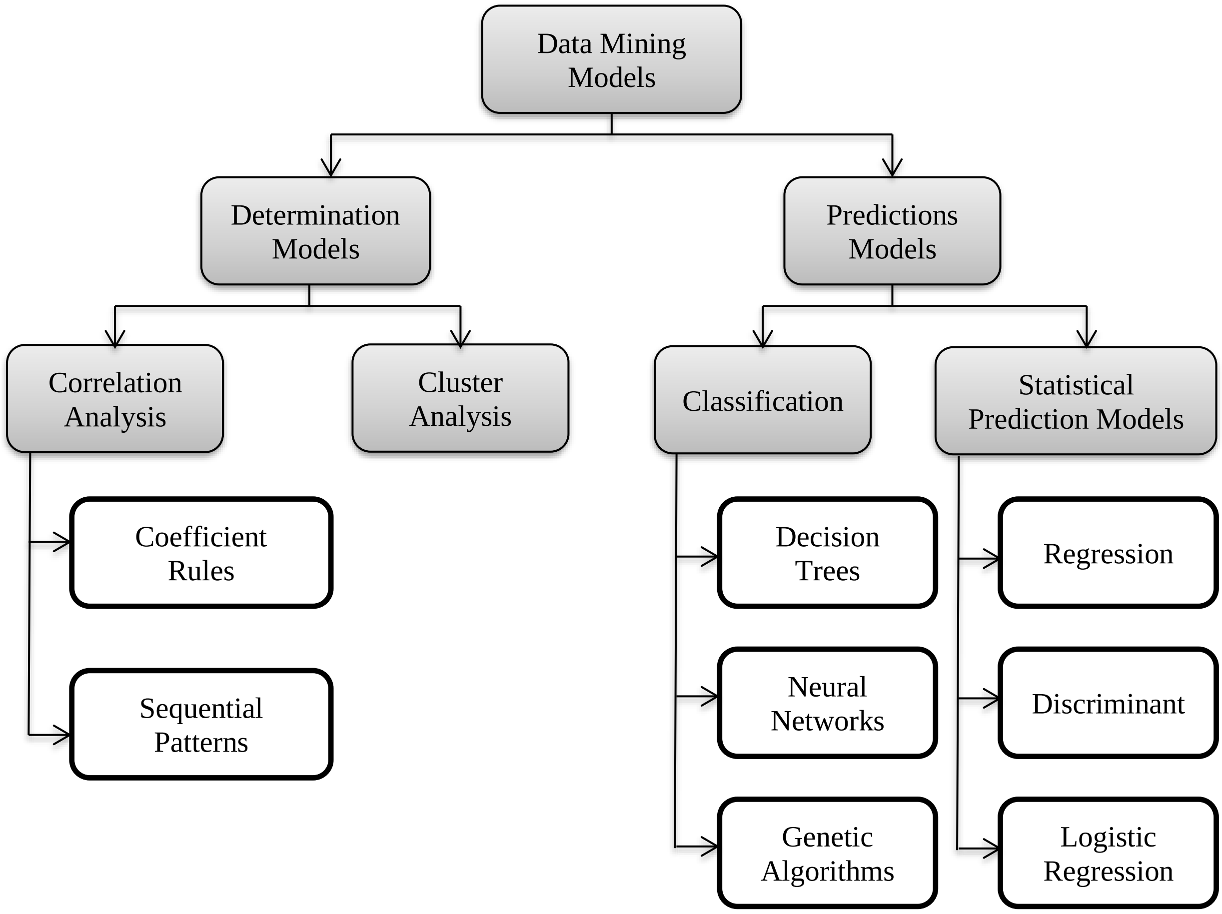

Figure 3. *Data Mining Models And Analyses*

As seen in Figure 3, descriptive models are categorized as correlation analysis and cluster analysis (Şimşek Gürsoy; 2009). Correlation analysis employs association rules and sequential patterns. Association rules define concurrent event series, while sequential patterns define successive event series. For example, "people who buy tourism and travel books would also buy a pocket dictionary with an 80% probability" is an association rule, while "people who buy a washing machine also buy a dryer within six months with a 90% probability" is a sequential pattern. Cluster analysis allows the acquisition of homogeneous groups through classification of the data based on a specific variable group (Han, Kamber & Pei, 2012).

Predictive models are scrutinized in the two groups of classification and statistical prediction models. Classification models employ decision trees, artificial neural networks and genetic algorithms. The decision trees analyze all actions that may be included in the dataset based on all aspects, and determine a classification of these actions, while artificial neural networks also generate and employ unknown data (Romero, Ventura, Pechenizkiy, & Baker, 2010). Genetic algorithms are described as a search method (Şimşek Gürsoy, 2009) employed to determine the most specific data in a data block, inspired by "survival of the fittest" in Darwin's theory of evolution. Statistical estimation techniques, another predictive model, employ regression, discriminant and logistic regression analyses, which have been coomonly used in the literature.

Data mining is frequently used in finance and marketing. Its functions such as revealing hidden patterns, classification, and prediction paved the way for employment in the field of education. The utilization of data mining in education led to the introduction of the concept of "educational data mining."

Educational Data Mining

Educational data mining developed with the adoption of data mining processes in education. Baker (2010) described educational data mining as a discipline that employs data in educational field to improve educational conditions and to better understand the student and the was students learn. However, it was observed that this description neglected data mining processes and analytical techniques. According to Calders and Pechenizkiy (2011), educational data mining is a learning science that employs the broad application field of data mining and an application that both develops and improves educational practices and learning material based on the findings obtained with educational data. Romero and Ventura (2010; 2013), on the other hand, defined educational data mining as an application where data mining techniques are employed on educational data to identify or solve significant educational problems. Based on these definitions, it could be suggested that educational data mining aims to contribute to the educational environment by employing educational data and data mining processes in educational data mining operations. Furthermore, Bousbia and Belamri (2014) argued that educational data mining does not only employ data mining but also the computer science, educational and statistical processes. It could be argued that these fields are not separate, but their interaction could serve several purposes in educational data mining. The above-mentioned case is presented in Figure 4.

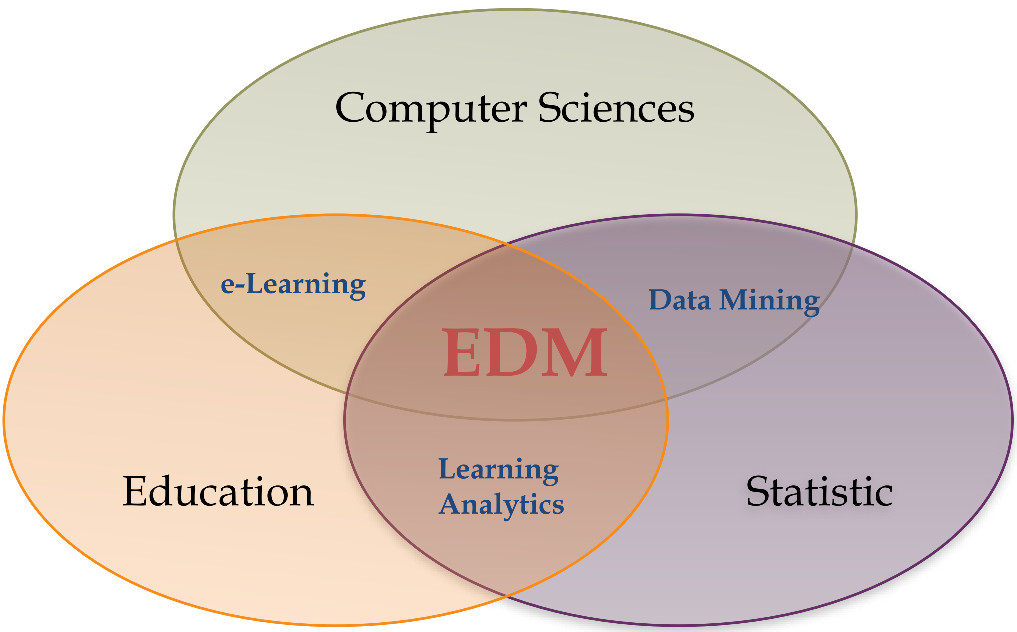

Figure 4. *The Fields in Educational Data Mining (EDM) (Bousbia and Belamri, 2014)*

As seen in Figure 4, educational data mining benefits from the interaction between several fields. Although the main fields include computer science, education and statistics, data mining is one of the main fields that educational data mining employs. Another field is lthe earning analytics.

Learning Analytics

Learning analytics was described as the measurement, collection, analysis and reporting of learner and context data to understand learning and the environment where learning occurs in hhe first Learning

Analytics and Knowledge (LAK) conference website (LAK'11, 2014). On the other hand, Elias (2011) desceribed learning analytics as a novel field where advanced analytical tools are employed to improve learning and education. According to Siemens and Gasevic (2012), learning analytics is the discovery of knowledge using data and various analysis models produced by students to predict learning and develop various recommendations. Johnson, Smith, Willis, Levine and Haywood (2011) suggested that learning analytics is the interpretation of big data collected by students with various methods to analyze the academic process, predict future performances, and determine potential problems. Apart from the differences in these descriptions, it was observed that the emphasis on the transformation of educational data into findings that could be useful in the advancement of learning by learning analytics was common (Chatti, Dyckhoff, Schroeder, & Thüs, 2012). Based on the fact that educational data mining provides information, findings or solutions for important problems in education and contributes to learning material, its confusion with learning analytics or inseparability of the concepts should be considered natural. The literature review revealed that the main difference was that although data mining processes are employed in educational data mining, the learning analytics processes are different from those of the data mining and educational data mining. This is a cyclical process that includes three steps: data collection and preprocessing, analytics and action, and post processing. This process is presented in Figure 5.

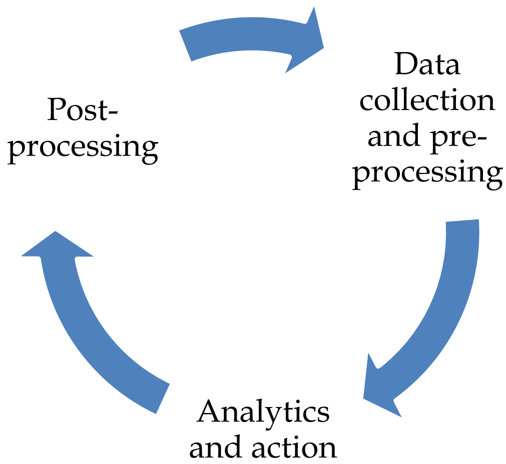

Figure 5. *Learning Analytics Process (Chatti et al., 2012)*

The cyclical process presented in Figure 5 includes three main stages. The first stage is the data collection and preprocessing phase. This stage includes preprocessing the data collected from various educational sources or systems, in other words, rendering the data suitable for the learning analytics method (Liu, 2006). In the analytics and actions stage, the patterns are explored, modeled and utilized. This process also includes processes such as observation, analysis, evaluation, compatibility testing, interpretation and model customization. These processes constitute the “actions” dimension of the stage (Han et al., 2012; Liu, 2006; Romero and Ventura, 2007). The final stage involves testing the adequacy of the model developed based on the acquired patterns using the data obtained from a new database. Considering the complexity and difficulty of the process, there is a need for a reference model that would facilitate the clarification of the actions in the steps described in the literature and for the researcher to develop a roadmap. The reference model, which serves as a road map in the learning analytics processes and developed by Chatti et al. (2012), is presented in Figure 6.

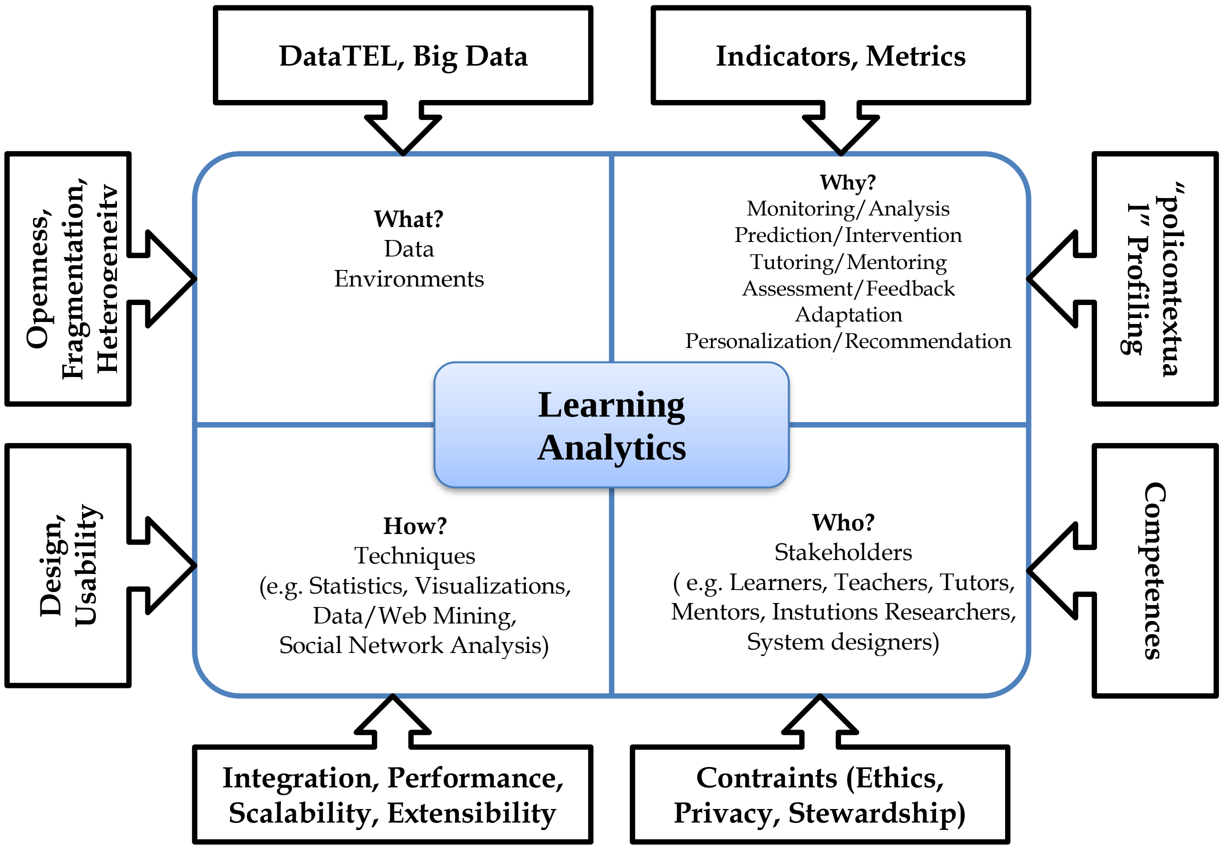

Figure 6. *Learning Analytics Reference Model* (Chatti et al., 2012)

The model presented in Figure 6 was based on four main questions: what, why, who and how. The process could progress by answering these four questions in learning analytics development. The boxes around the figure represent various difficulties and research opportunities that emerge when the questions are answered. The big data patterns are obtained based on these questions and the model. In distance learning, several records such as logs of students' interactions with the system, their personal and demographic information, instructor interaction and products, system-specific data could be kept and these records constitute the big data. Patterns that could be obtained from the distance learning big data could contribute to the system in many ways. However, they also lead to certain limitations.

The aim of the present study was to analyze the role of learning analytics in education by discussing the phenomenon of learning analytics in detail. Especially, these pandemic days, distance learning have a big importance than ever before. Instructional designers, administrators, faculty mambers, tezchers etc. stakeholders of learning are making a big effort to increase effectiveness of distance learning. At this point, it can be said that this study can support their design process and give them a guideline. Thus, SWOT (Strengths, Weaknesses, Opportunities, Threats) analysis was cınducted in the study. SWOT analysis aims to determine the current status of an act, a situation or a product, and tu guide R&D studies (Dyson, 2004; Pickton and Wright, 1998). In this analysis, the existing data are analyzed by asking questions about the internal factors that would reveal the strengths and weaknesses of the data, and about the external factors that would lead to opportunities and threats, and a table of four dimensions is developed (Kurtilla, Pesonen, Kangas and Kajanus, 2000). During this analysis, various data such as historical statistics, documents, purposive data, and analytics could be employed as a resource (Chang and Huang, 2006; Kumar, Dabas and Hooda, 2018).

CONCLUSION AND RESULTS

The data source for the SWOT analysis conducted in the present study included documents. For this analysis, initially, a literature review was conducted and the role of learning analytics in the distance learning system was detailed with the analysis of available studies in the literature. In the study, accessed electronic data were analyzed. Since the topic was current and most relevant studies were conducted in the last decade, the period of review was not limited. Web of Science, ERIC, Google Scholar and Turkish National Dissertation data bases were reviewed. Reached 37 studies, which were searched learning analytics in distance learning, were examined in the perspective of SWOT. However, there is a SWOT analysis study on learning analytics, conducted by Papamitsiou ve Economides at 2014. But they did not limit their issue with distance learning context or any area. Thus, studies that utilized learning analytics in distance learning, and those that included learning analytics recommendations for problems encountered in distance learning were included in the analysis. The analysis results are presented in Table 1.

Table 1. *SWOT Matrix*

	STRENGHTS	**WEAKNESSES**
Internal factors	- Flexible and innovative design - Rising effectiveness - Induvidualisation of learning or system - Understanding user expectations	- Determining parameters - Lack of experts
	Oppurtunities	**Threats**
External factors	- Development in artifical intelligence - From globalisation to localisation change trend - Gathering big data easily	- Ethical issues (security of data, accessing data, private information etc.) - Information consumption

As seen in Table 1, the strengths of the employment of learning analytics in distance learning were significantly higher. However, while learning analytics is employed in distance learning, certain action should be planned without ignoring the remaining concerns. Thus, the matrix determined in the study should be addressed based on the internal and external factors. Internal factors are those inherent in learning analytics and distance learning. More specifically, they are directly associated with the design. Thus, they are easy to employ and control. The products of learning analytics applications in distance learning significantly affect the design of learning environments (Bahçeci, 2015; Clow, 2012, Siemens, 2012). Previous studies revealed that flexible and innovative learning environments could be designed (Ferguson and Shum, 2012; Khalil and Ebner, 2017; Şahin and Yurdugül, 2020) in distance learning with learning analytics. Learning analytics is one of the most modern approaches that could be employed in 21st century learning. The non-innovative elements that are not interesting for the learners could be identified and eliminated in the design. There are studies which suggested that the employment of learning analytics improves the productivity in distance learning (Olmos and Corrin, 2012; Smith, Lange and Huston, 2012; Şahin and Yurdugül, 2020). Similarly, learning analytics that could provide a detailed analysis of learner and faculty member preferences and designs leads to a more efficient content design, timing and planning. Another strength was the ability to customize the learning or the system with learning analytics in distant education (Bozkurt, 2016; Ezen-Can, Boyer, Kellogg and Booth, 2015; Greller and Drachsler, 2012; Kilis and Gulbahar, 2016; Wilson, Watson, Thompson, Drew and Doyle, 2017).This was due to the that most analyzed big data were obtained from the learners, which easily provide information about the learner preferences., facilitating the customization of the designs. Similar to all educational processes, distance learning systems should meet 21st century learning expectations (Clow, 2012; Fulantelli, Taibi and Arrigo, 2013). However, it is necessary to determine expectations. Learning expectations vary based on content, quality, and innovation (Gazulla and Leinonen, 2016; Hickey, Kelley and Shen, 2014). Learning analytics provides convenience in this process. To be more specific, learning analytics in distance learning has certain strengths (Clow, 2012; Herodotou et all., 2017) in determining the expectations of system users and stakeholders such as learners, faculty members, and administrators.

When learning analytics is employed, the parameters that could obtain the patterns are determined. Big distance learning systems data could be quite complex. It is not always possible to determine the parameters that could produce a purposive pattern based on the data (Agudo-Peregrina, Iglesias-Pradas, Conde-González, and Hernández-García, 2014; Macfadyen and Dawson, 2012). Furthermore, not all determined parameters could produce purposive patterns. For example, in big data analysis, one of the important parameters in the "interaction and learning" pattern could be "the learner preferences." Failure to identify these cases well may result in a failure to produce efficient information with the collected data. However, one of the important weaknesses in conducting learning analytics in distance learning based on the collected literature data could be the lack of experts in the field of learning analytics (Fırat, 2015; Macfadyen and Dawson, 2012; Wilson, et all. 2017). However, it could be suggested that important developments could be observed towards the solution of this problem as learning analytics becomes more popular. The comparison of the internal factors based on strengths and weaknesses revealed a significant finding that the number of strengths were higher in the literature. Thus, it could be suggested that the aspects of learning analytics that could be used in distance learning were high.

External factors are associated with external stakeholders that affect the design of learning analytics in distance learning. Utilizing or controlling these factors require a more planned approach and efforts. External factors are analyzed in two groups: opportunities and threats. The literature review revealed that the reflections of the advances in artificial intelligence on education led to positive conditions for the use of learning analytics in distance learning (Alonso and Casalino, 2019; Bajracharya, 2019). Learning analytics patterns and artificial intelligence algorithms are basically similar. Thus, learning analytics applications in distance learning could support artificial intelligence applications in distance learning. It is inevitable that the artificial intelligence trend would increase the significance of learning analytics. Especially due to the pandemic, a trend from globalization to localization has already started. Digital globalization continues, but individuals prefer a change towards localization in their daily lives, economic order, education systems etc. Thus, it would be important to reveal various traits of individuals and develop designs that are suited for the individual rather than the general. For this purpose, learning analytics promise significant benefits for distance learning systems (Fulantelli, et all., 2013; Kalz, 2014; Siemens, 2012). As mentioned above, the big data required for learning analytics could easily be obtained from distance learning systems (Tabaa and Medouri, 2013).

The most important risk in the application of learning analytics in distance learning is ethical problems (Bozkurt, 2016; Prinsloo and Slade, 2013, 2015). There are significant ethical issues such as which information is private, which pattern violates confidentiality, and the protection of big data. These risks pose major threats. Necessary measures should be taken to provide data security, protection and storage of personal data (Bozkurt, 2016; Prinsloo and Slade, 2013, 2015). Furthermore, the rapid consumption of information, the short-term validity of the produced information, in other words, the short life span of the information are the other risks mentioned in the literature (Macfadyen and Dawson, 2012). Today, the information is produced, structured and consumed very quickly, and there is also a risk of rapid consumption of these analytics, which were acquired with great effort and attention to detail. The effectiveness of the distance learning design developed with the pattern produced with this scenario could be discussed as well.

Instructional design process begins with needs analysis. It continues with formative analysis during the process and summative analysis after the process (Merrill, 1991; Reigeluth, 2013; Sweller, 1999). Most instructional design models prioritize formative evaluations (Reigeluth, 2013; Reiser, 2001). As is known, since each evaluation is based on a measurement or observation, data are collected and analyzed during the evaluation process. The most important benefit of learning analytics in distance learning is the analysis of instructional design processes (Bayrak and Yurdugül, 2016; Chatti, et all., 2012; Mattingly, Rice and Berge, 2012). This is the most important reason behind the SWOT analysis conducted in the study. Strengths of learning analytics could be considered as an indicator of its significant role especially in formative assessment. Thus, the benefits of analyzing learning analytics in the context of distance learning are indisputable. It could be suggested that the present study provided a framework that could guide the decisions of distance learning designers on stakeholders. Thus, it was considered that the study provides a roadmap for distance learning practitioners and researchers that could be beneficial in decision making and system improvement.

Based on the SWOT matrix, it could be suggested that strengths and opportunities of learning analytics were more dominant when compared to its weaknesses and threats in distance learning. It is highly functional when threats are kept under control in the process of instruction design and design improvement (Dyckhoff, Lukarov, Muslim, Chatti and Schroeder, 2013). Thus, it could be suggested that a learner-centered education system could benefit from learning analytics outcomes in developing a learner-oriented design. The contributions of the learning analytics to both content design and the requirements of faculty members are obvious. However, internal and external adverse factors mentioned in the literature should also be checked by administrators and decision makers and these parties should take necessary precautions.

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