Evaluating Big Data Use in Educational Institutions Using Fuzzy Multi-Criteria Decision-Making Approach

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Abstract:

Educational institutions are now days rely on the Big Data; therefore, it is important for decision makers to make helpful use of the Big Data, which is a multi-criterion decision-making problem (MCDM). To address this MCDM problem, we conducted expert's evaluation using Fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) of three Saudi public Universities regarding the use of their Big Data. This paper aims to evaluate the strength for the Big Data use from student learning, teaching and administration factors.

Keywords: evaluating, big data, multi-crtiteria, decision making, approach.

تقييم استخدام البيانات الضخمة في المؤسسات التعليمية باستخدام مدخل متعدد المعايير لاتخاذ القرار

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ملخص:

المؤسسات التعليمية أصبحت تعتمد على البيانات الضخمة مؤخراً. لذلك من المهم لصناع القرار في المنظمات التعليمية بشكل عام والجامعات بشكل خاص تبني التقنيات والأدوات المساعدة للإستفادة من البيانات الضخمة في إتخاذ القرارات لتطوير جميع الجوانب المتعلقة بالعمليات التعليمية. إن التعامل مع البيانات الضخمة لإتخاذ القرارات المناسبة يعبر عنه علمياً بأنه مشكلة, وتسمى هذه المشكلة (مشكلة اتخاذ القرارات متعددة المعايير MCDM). ولمعالجة هذه المشكلة (MCDM)، أجرينا تقييمًا بواسطة بعض الخبراء باستخدام تقنية Fuzzy TOPSIS (تقنية ترتيب الأفضليات عن طريق التشابه مع الحلول المثالية) لثلاث جامعات سعودية حكومية فيما يتعلق باستخدام بياناتها الضخمة. هذا البحث يهدف إلى تقييم قوة استخدام البيانات الضخمة في المنظمات التعليمية من عوامل تعلم الطلاب والتدريس والإدارة.

الكلمات المفتاحية: التقييم، البيانات الضخمة، متعدد المعايير، اتخاذ القرار، المدخل.

1. Introduction

A phenomenon in which there is a vigorous and multi-faceted growth in data is referred to as Big Data. Structural as well as functional facets are used by researchers to hypothesize Big Data. The aspects of volume, variety, veracity, velocity, value and verification are part of the structural dimension of Big Data (Poulovassilis, 2016). The reason for the structural variability and complexity of Big Data is that social media applications, sensor networks and other mobile and universal devices have given rise to new types of data (Manyika et al., 2011; Ward and Barker, 2013). In addition, using innovative technologies to gather, preserve, disseminate, regulate and assess bigger and heterogeneous datasets has been defined in the functional dimension (Dede, Ho, & Mitros, 2016).

Big Data in education is the latest research domain that brings about novel means of formulating research questions, developing studies, assessing and visualizing data (Daniel, 2015). As extensive amounts of data are present in the field of education, it becomes possible for researchers to examine subgroups of a population (a specific group of people), without having to depend on complex probabilistic techniques (Mayer- Schonberger, 2015). In addition, researchers are able to obtain extensive amounts of research data by incurring a comparatively lower cost when they make use of Big Data tools (Mayer- Schonberger, 2015). Educational researchers gain access to a wide variety of tools through Big Data, which enables them to use and envisage data in the field of teaching and learning (Baker & Siemens, 2013; Bhat & Ahmed, 2016).

Greer and Mark (2016) suggested that visualization methods help in determining significant patterns within educational data that the teachers using traditional statistical techniques may not be able to identify. It has also been shown in research that the teachers that have very little mathematical knowledge may be easily able to navigate and understand student data with the help of visualization dashboards (Bueckle et al., 2017; Ong, 2015;

Sohaib et al. 2019). Technology readiness has positive influence on students learning (Dolmark et al. 2019). When a large set of educational data is evaluated, the formulation of predictive models for determining opportunities and dealing with the problems of educational institutions is brought about (Daniel & Butson, 2013). It has also been asserted that the information obtained from predictive models can help in assessing student learning patterns, which would help in the development of adaptive and customized learning settings (McKenney & Mor, 2015).

The analysis of student data has turned into a significant phenomenon in recent times (Lodge & Corrin, 2017). Nonetheless, it seems that the studies on artificial intelligence in education led to the use of data to facilitate student learning. Data is mainly used in the present times in education to recognize strategies that will enable the development of improved conditions for learning (Mor, Ferguson, & Wasson, 2015). Big Data in education is a relatively new trend that comes about due to the presence of significant amount of educational data that is stored in established databases (such as the data acquired from social media and learning management systems). However, it is possible that educational research will turn into a data-intensive field that employs techniques and approaches from Data science. The focus of Data science is to develop and utilize tools and procedures for obtaining and identifying significant knowledge from complex data (Waller & Fawcett, 2013). It was indicated by Kalota (2015) that academic bodies are able to comprehend the issues encountered by students and come up with relevant strategies to deal with them due to the Big Data approaches.

The objective of the education sector is to improve the learning experience, the effectiveness of the instructor, and to offer relevant, effective and efficient teaching and learning conditions that are in accordance with the abilities and resources of the learner (Wang et al. 2018). An important part was played by Big Data and mass education to create expectations for achievements, accountability and access that is imperative for the establishment

of smart societies. To achieve this, infrastructure and capability for sustainable change needs to be offered so that to bring about the institutionalization of knowledge generation, acquisition and sharing development (Popovič et al. 2018). As extensive educational data is available, educational researchers are offered the opportunity to use automated tools and techniques to examine intricate educational events on a large scale. Also, the knowledge sharing then impact the organization performance (Attar et al. 2019; Alharthy et al. 2018).

1.1 Big Data Assessment in Higher Education

Research has shown various views on what comprises Big Data in the higher education sector. Such as Daniel and Butson (2013) described Big Data in higher education consists of institutional analytics, information technology analytics, academic analytics and learning analytics. Institutional analytics deals with administrative data analysis to enhance the quality of decision-making process. Information technology analytics refers to the data analysis related to administrative and student use of technology services.

Furthermore, academic analytics is the data analysis on academic programs performance. The outcome of academic analytics is used for strategic decisions making involving the facets of administration (Siemens, 2013). Learning analytics deals with the data analysis students and the environment in which learning occurs. The outcome of learning analytics is used to understand and improve the process of students learning (Siemens, 2013). Three educational uses of Big Data were put forward by Daniel (2015; 2019), which are supporting administration, teaching and learning. This study focuses on these three aspects to understand the process of students learning in Saudi higher education context.

This variety of Big Data conception in the higher education sector shows a multiple criteria decision-making (MCDM) problem. This means making a preference decision is characterized by multiple criteria from a set of available alternatives. There are many

having many MCDM methods (Sohaib et al. 2019). However, the TOPSIS method developed by Hwang and Yoon (1981) is a popular method representing the reasoning of individual choice.

1.2 Problem Statement

At present, e-learning communities, online chatrooms and discussion forums, Flipped Classroom and Moodle have brought about a reformation in the education, leading to an improvement in the learning experience. In addition, mobile computing is low-cost learning with the help of smart digital devices and mobile phones. Nonetheless, a large amount of data is made available, while conventional methods are restricted to processing the traditional data application. Hence, the use of Big Data analytics became prevalent in institutions to handle educational data.

The use of Big Data by the Saudi education sector will enhance student services, which comprise of generating students understanding, improving performance, results and retention of students, as well as tailoring the teaching, learning and assessment techniques to make it consistent with the needs and potential of students within the specified resources. However, Big data is frequently required to achieve the outcomes of educational research so that certain learning issues can be managed. Hence, it is imperative to determine to evaluate the comprehensive strength for the Big Data use in Saudi Universities.

1.3 Research Objective

This paper aims to evaluate the comprehensive strength for the Big Data use in Saudi public Universities based on Daniel (2015; 2019) research on Big Data in Education. Considering the imprecise judgments of decision makers, the fuzzy TOPSIS is will be used for the evaluation of Saudi universities. The Fuzzy TOPSIS method is explained in detailed in section 2.2. The results will rank the University based on the Big data generated from supporting learning, teaching and administration factors.

1.4 Research Question

Following the objective of the study, the research question this study address: How the Big Data is used for students learning and support in Saudi Universities?

1.5 Contribution of the study

The use of Big data in education is a latest trend (Picciano, 2012), where majority of the studies focus on the use of data to determine the quality of teaching and research being carried out (Eynon, 2013). However, this study fills the gap by focusing on students Big Data. This research will comprehend the issues encountered by students and come up with relevant strategies to deal with them due to the Big Data use.

The paper is structured as follows: Section two provides the background information and related studies. Then it presents the methodology in Section three followed by case study results in Section four. Finally, the Section five provides some discussion and the study concludes.

2. Theoretical Background

2.1 Big Data in Higher Education

Big data is a large data sets that are computationally analysed to find significance related to humans. The aspects of volume, variety, veracity, velocity, value and verification are part of the structural dimension of Big Data (Poulovassilis, 2016). In the education sector, Big Data analytics comprises of Data Analytics, Data Mining and Web Dashboards. Data collection and analysis of evidence-based learning automated instructions and assessment environments is brought by Big Data analytics (Xing & Du, 2018). It helps in obtaining extensive information so as to ensure best practices that enhance profitability and productivity.

Big Data analytics is now being utilized by the education sector with the intention of enhancing their services, which comprise of generating understanding, improving performance, results and

retention of students, as well as tailoring the teaching, learning and assessment techniques to make it consistent with the needs and potential of students within the specified resources. Nonetheless, it is frequently required to achieve the outcomes of educational research so that certain learning issues can be managed.

Hence, it is imperative to determine the reasons why issues are faced, instead of just explaining problems so that improved strategies can be developed to accomplish the required educational results. According to Romero and Ventura (2010), researchers in higher education have used considerably lower amounts of data, which has restricted its interpretative power, validity and latency. When researchers use Big Data in education, they are provided with powerful approaches through which they can identify subtle population tendencies that may not be accomplished with small-scale data (Fan et al., 2014). Nonetheless, the results of Big Data research depend on correlational models and predictive assessments, because of which the causality of educational research outcomes is sought, but unachievable to a certain degree.

The previous studies have also present different sources of Big Data in Education (Bamiah et al. 2018). For instance, different sources of Big Data in education were presented by Poulovassilis (2016), such as data created and stored in virtual learning systems, student personal records, assessment data, video data and learner models. Dashboard can be utilized by teachers to envisage student learning patterns and determine those aspects where the greatest issues are faced by students so that improved intervention strategies can be developed.

In a similar way, when students are provided access to the customized dashboards, a higher sense of self-awareness is generated among students, leading to self-guided learning dispositions (Tan et al., 2017). Studies have been carried out on the relationship between correlation and causality (Mayer-Schonberger, 2015). It has been asserted by Mayer-Schonberger

(2015) that when correlational analysis of Big Data research is carried out, it can generate valuable relationships for formulating interventions even when causality is lacking. Nonetheless, when correlation is considered as causality, the possibility of selecting ineffective interventions increases, even when this outcome depends on the assessment of an extensive dataset.

2.1.1 Learning Analytics

The use of Big data in education has been examined in various studies. Williamson (2017) and Klašnja - Milićević (2017) and Swing (2018) and Shah (2018) studied the use of big data in education and offered information on learning analytics and how these can be used practically. A few of these comprise of institute quality management (Khan and Alam, 2017), management (Baker & Inventado,2014), student performance prediction (Sin & Muthu, 2015), estimate of student dropout and online education applications (Niemi & Gitin 2012). Teachers can also use learning analytics to determine risk factors related to the involvement of students in learning and to enhance the way learning environments are designed (Lodge & Corrin, 2017). Taking this into consideration, these applications are all suggestions and the research in this field has not yet commenced.

The two key areas that were recognized were educational Data Mining and learning analytic (Williamson, 2017). Educational Data Mining is used to assess the behaviours and performances of the learners (Prakash, 2014). It helps in assessing the learning procedures by using automated interactive intelligent systems, learning management systems to analyse how they interact with the learning environment (Williamson, 2017).

Big data helps in improving the education process and bringing about better outcomes, in addition to operational productivity and success. Nonetheless, there are still various issues that are faced, such as privacy, security, well-timed examination of data, ethical considerations, efficient data gathering, storage, distribution and visualization (Brohi et al. 2016; Hossain, 2015). Big Data in

education helps Universities to understand challenges and identify strategies to address them. Daniel (2015) suggested three uses of Big Data in Education, which are teaching, administration and students learning. For the purpose of this study we have adopted Daniel (2015; 2019) use case scenarios in Big Data education (Figure 1).

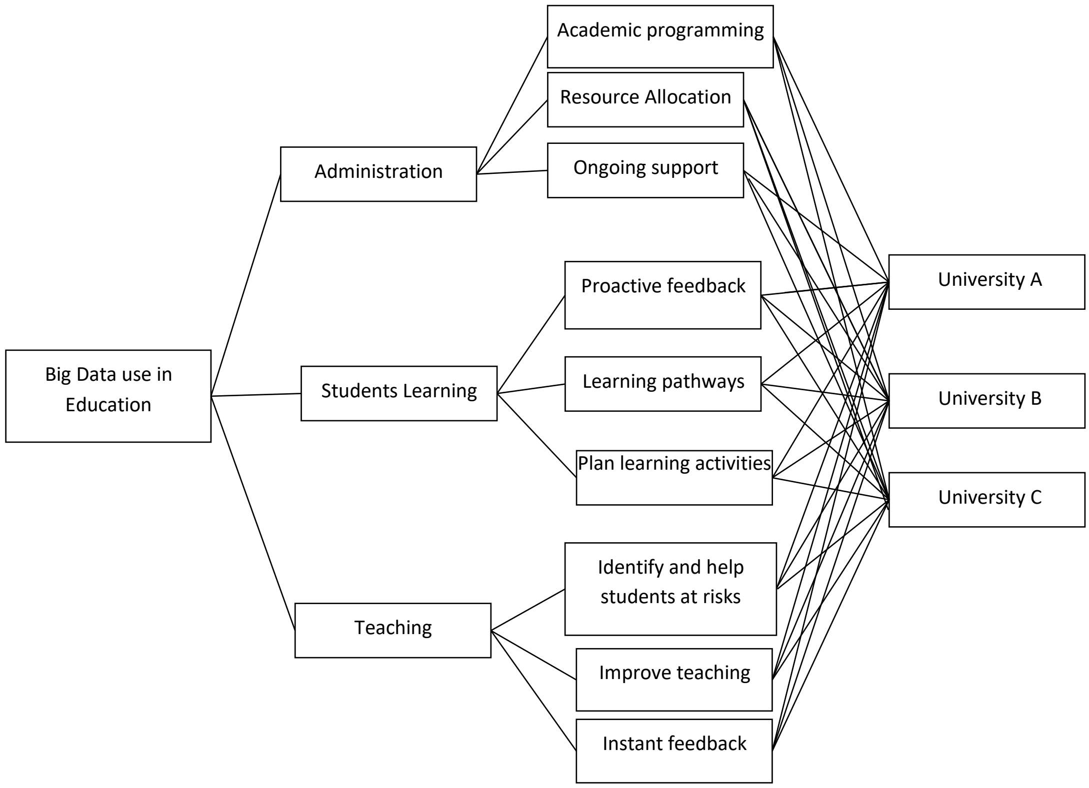

Figure 1: The hierarchy of the Big Data Use in Education (Daniel, 2015; 2019).

2.2 Multi-Criteria Decision Making – Fuzzy TOPSIS

Multi-criteria decision-making (MCDM) is the decision making in the presence of multiple criteria (Lu et al. 2015; Mardani et al. 2015). There are many MCDM approaches for choosing the best

feasible option. However, due to fuzziness in criteria and decision makers' judgments, the fuzzy technique for order preference by similarity to ideal solution (TOPSIS) Hwang and Yoon (1981) to deal with the decision-making problem is widely used. TOPSIS is applied in different application areas (Sohaib et al. 2019; Sohaib and Naderpour, 2017; Sohaib et al. 2018). The following steps explain MCDM and the TOPSIS problem (Sohaib et al. 2018).

MCDM problem is based on *m* alternatives $(A_1, A_2, \dots, A_m)$ and *n* criteria $(C_1, C_2, \dots, C_n)$ is presented as: (1)

$$X = [x_{ij}]_{m*n}\,, W = [w_j]_n$$

where *X* is the decision matrix, x_{ij} is the performance of the *i*th alternative with respect to the *j*th criterion, *W* is the weight vector, and w_j is the weight of the *j*th criterion. In fuzzy MCDM both *X* and *W* are linguistic terms that are presented by fuzzy numbers and defining appropriate membership functions. For example, $\tilde{X} = \{\tilde{x}_{ij}, i = 1,2, \dots, m, j = 1, \dots, n\}$ is the linguistic for alternatives with respect to criteria, and $\widetilde{W} = \{\widetilde{w}_j,\ j = 1, \dots, n\}$ is the linguistic vector of criteria weights. The fuzzy TOPSIS steps are as follows:

<u>Step 1:</u> $\tilde{x}_{ij}$ is normalized fuzzy decision matrix that normalized triangular fuzzy numbers belong to [0,1]; so, there is no need for normalization.

<u>Step 2:</u> The weighted normalized fuzzy decision matrix is calcutated as:

$$\tilde{V} = [\tilde{v}_{ij}]_{m*n}\ i = 1, \dots, m, j = 1,2, \dots, n \qquad (2)$$

where $\tilde{v}_{ij} = \tilde{x}_{ij} \otimes \widetilde{w}_j$ is the standard multiplication of two triangular fuzzy numbers. Assume $\tilde{a} = (a_1, b_1, c_1)$ and $\tilde{b} = (a_2, b_2, c_2)$, then

$$\tilde{a} \otimes \tilde{b} = (a_1 a_2, b_1 b_2, c_1 c_2) \qquad (3)$$

<u>Step 3:</u> Identification of fuzzy positive ideal and fuzzy negative ideal solutions are measured as follows:

$$A^{+} = \{\tilde{v}_1{}^{+}, \tilde{v}_2{}^{+}, \dots, \tilde{v}_n{}^{+}\} = \{(\max_j \tilde{v}_{ij} | i \in I') \, or \, (\min_j \tilde{v}_{ij} | i \in I'')\} \; i = 1, \dots, m \;\; j = 1, \dots, n \quad (4)$$

$$A^{-} = \{\tilde{v}_1{}^{-}, \tilde{v}_2{}^{-}, \dots, \tilde{v}_n{}^{-}\} = \{(\min_j \tilde{v}_{ij} | i \in I') \, or \, (\max_j \tilde{v}_{ij} | i \in I'')\} \; i = 1, \dots, m \;\; j = 1, \dots, n \quad (5)$$

where I' is related with benefit criteria and I'' is related with cost criteria.

<u>Step 4:</u> The distance of each alternative from fuzzy positive ideal and fuzzy negative ideal is determined as:

$$D_j^{+} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_i{}^{+}) \qquad j = 1,2, \dots, n \quad (6)$$

$$D_j^{-} = \sum_{j=1}^{n} d(\tilde{v}_{ij}, \tilde{v}_i{}^{-}) \qquad j = 1,2, \dots, n \quad (7)$$

where $d(\tilde{a}, \tilde{b})$ is the vertex method that calculates the distance between two triangular fuzzy numbers $\tilde{a}$ and $\tilde{b}$:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \quad (8)$$

<u>Step 5:</u> The similarities to fuzzy positive ideal is calculated as:

$$C_j = \frac{D_j^{-}}{D_j^{+} + D_j^{-}} \qquad j = 1,2, \dots, n \quad (9)$$

<u>Step 6:</u> Finally, the rankings are calculated. The alternatives are ordered based on C_j in descending. The alternative with highest C_j is considered the best choice.

3. Methodology

The criteria are to evaluate the Big Data use in Saudi public Universities. Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method is used to evaluate the different

alternatives. TOPSIS steps are defined in above section 2.2. The TOPSIS method developed by Hwang and Yoon (1981) is a popular method to define positive and negative ideal solutions of the chosen alternatives. The criteria are evaluated by three experts using weighting criteria as shown in Table 1. Three experts evaluated the alternatives (three universities) with the designed linguistic terms as shown in Table 2. Then finally fuzzy TOPSIS is applied to rank the alternatives. Figure 2 shows the proposed method steps. The following section explain the method with case study implementation.

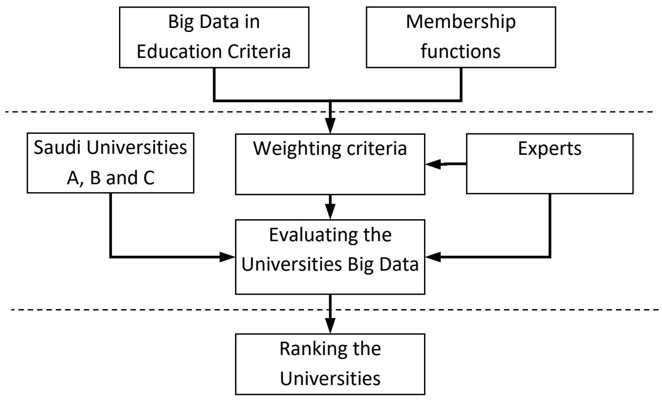

Figure 2. The proposed methodology.

3.1 Research Population and Sample

The population of this study consists of Saudi universities. The data sample is collected from three large public Saudi Universities. An executive group, consisting of decision makers from all three Universities were invited for survey.

3.2 Research Procedure

The Big Data use in education is determined based on use case scenarios of Big Data in education provided by Daniel (2015; 2019). The triangular fuzzy numbers are used to express the importance of each criteria. The linguistic variables proposed by

Chen and Hwang (1992) are used for weighting criteria as represented in Table I.

TABLE I. FUZZY LINGUISTIC TERMS AND FUZZY NUMBERS FOR WEIGHTING CRITERIA

Linguistic term	Fuzzy number
Very low (VL)	(0, 0, 0.2)
Low (L)	(0.05, 0.2, 0.35)
Medium low (ML)	(0.2, 0.35, 0.5)
Medium (M)	(0.35, 0.5, 0.65)
Medium high (MH)	(0.5, 0.65, 0.8)
High (H)	(0.65, 0.8, 0.95)
Very high (VH)	(0.8, 1, 1)

Similarly, Table II illustrates each fuzzy linguistic term to its correspondent triangular fuzzy numbers.

TABLE II. FUZZY LINGUISTIC TERMS AND FUZZY NUMBERS FOR EVALUATING ALTERNATIVES

Linguistic term	Fuzzy number
Not exist (NE)	(0, 0, 0)
Very poor (VP)	(0, 0, 0.1)
Poor (P)	(0.05, 0.2, 0.3)
Medium poor (MP)	(0.2, 0.3, 0.5)
Fair (F)	(0.3, 0.5, 0.6)
Medium good (MG)	(0.5, 0.6, 0.8)
Good (G)	(0.6, 0.8, 1)
Very good (VG)	(0.8, 1, 1)

The experts evaluated the alternatives with the designed linguistic terms and determine the Universities choices for evaluation. The

fuzzy TOPSIS presented in above section is applied to rank the alternatives.

3.3 Case Study

This study intends to evaluate the Big Data use in three Saudi Universities. All three universities are a well-known public university in Saudi. An executive group, consisting of three decision makers DM1 to DM3 from three different Universities were invited to survey three alternatives. The name of the Universities and the experts are preserved to keep the confidentiality. There are nine criteria and the experts assigned a linguistic term to represent the importance of each criteria as shown in the Table III.

TABLE III: CRITERIA AND CORRESPONDING WEIGHTS

Criteria	Symbol	DM1	DM2	DM3
Academic programming	C1	MH	H	H
Resource allocation	C2	L	M	H
Support ongoing efforts	C3	L	M	H
Proactive feedback	C4	H	M	M
Learning pathways	C5	VH	H	MH
Plan learning activities	C6	MH	H	M
Identify and help students at risk	C7	MH	H	H
Improve teaching	C8	ML	MH	M
Providing instant feedback	C9	H	MH	MH

The expert then evaluated the alternatives against each criterion. The fuzzy decision matrix is shown in Table IV.

TABLE IV: FUZZY DECISION MATRIX

Criteria		DM1	DM2	DM3
C1	Uni. A	G	VP	VP
	Uni. B	VG	G	MG
	Uni. C	VG	G	MG
C2	Uni. A	VP	MP	MG
	Uni. B	VG	MP	MG
	Uni. C	MG	VP	VG
C3	Uni. A	MP	MP	F
	Uni. B	MP	MG	VG
	Uni. C	MP	MP	MP
C4	Uni. A	G	MP	G
	Uni. B	G	MG	MG
	Uni. C	VG	G	MG
C5	Uni. A	VG	G	MG
	Uni. B	MG	MG	G
	Uni. C	F	MP	VG
C6	Uni. A	F	MP	F
	Uni. B	F	MP	VG
	Uni. C	G	MP	MP
C7	Uni. A	F	P	VP
	Uni. B	MP	MP	G
	Uni. C	P	P	VP
C8	Uni. A	VG	G	MG
	Uni. B	P	F	MP

	Uni. C	MP	P	VP
C9	Uni. A	F	P	G
	Uni. B	VG	G	G
	Uni. C	VG	G	VP

According to the fuzzy TOPSIS when applied, the fuzzy positive ideal and the and fuzzy negative ideal solutions are determined. The results show that University A is the best in terms of Big Data use in Education.

TABLE V: FUZZY TOPSIS RESULTS.

	Uni A.	Uni B.	Un. C
Distance D_j^+	25.47	27.68	26.66
Distance D_j^-	8.65	6.25	7.3
C_j	0.25	0.18	0.21
Rank	1	3	2

4. Discussion - Recommendations

The findings of the study show that it is vital to implement Big Data analytics in higher education due to extensive guidelines, competition, assessments and accreditation. It is highly likely that decision makers make critical decisions on the basis of the valuable information obtained after data analysis has been carried out. They concentrate on the intelligent outcomes of the institution to determine the learning success rate of the learners, patterns and challenges, in addition to their academic advancement. A significant amount of educational data is handled in Big Data analytics to assess and monitor the learners' records. Big Data analytics can be used to monitor the progress of learners, in addition, to their ensuing course results and dropouts. It generates a new paradigm for the stakeholders to choose the best practices that restructure teaching processes, and make sure that the

responsibility of the learners' satisfaction, attritions and success lies with the institutions.

Big Data allows decision makers to identify, comprehend, examine and forecast the behaviours of learners, the progress of educators and the course results, in addition to other institutional functions. For instance, it is possible to examine the behaviour of learners in an online learning environment when they are playing educational games, involved in the off-task behaviour or when they are unable to accurately respond to a query, even though they have the desired skill, or take extra time to respond. It is also possible to assess their rate of involvement when they are present in the discussion forums. Through this analysis, the learners' shortcomings and strengths can be determined, as well as who is going to be successful or unsuccessful. To use other techniques, learners are gathered and grouped on the basis of problems they face during learning and ways of interacting so as to assess their use of learning management systems to determine further course of actions and resources (Amershi and Conati, 2009; Yang et al. 2017).

4.1 Recommendations and Suggestions

This research provides some recommendations for the Saudi Universities based on the findings.

- **The errors in courses, programs and contents can be identified and monitored through Big Data analytics so that the curriculum being offered can be enhanced by offering data analytics and rich information regarding the data that has been created and collected (Khan et al. 2016).**
- **Customized instructions, responsive formative evaluations, actively involved pedagogy and collaborative learning are offered by Big data analystics, which helps in envisaging the performance of leaders depending on the evaluation of their history as a marker of future grades. Furthermore, it helps in monitoring the module progress report to recognize the issues faced while explaining the related subjects (Sin & Muthu,**

2015; Liñán and Pérez, 2015; Manohar et al. 2016). For instance, Moodle are used to obtain information regarding the courses and monitor the involvements, relations and submissions of students, as well as making live presentations or undergoing real-time quizzes over the internet.

- Big data in the education consists of main players such as faculty members, students, non-teaching instructors, and the overall organization. It is possible to further disintegrate student data into data relevant to the personal profiles of students, their performance score, attendance and assessment reports for extra-curricular and sports activities. Apart from this, student data also includes the data of those students who have completed their education and are part of the alumni. Future work should explore these issues and identify strategies to support students' activities.
- Big Data analytics is part of the National Education Technology model of United States Department of Education for the 21st century learning plan that seeks to enhance the quality of instruction provided (Bienkowski e al. 2012). The Saudi Universities should also follow a similar model to enhance the student experience.

4.2 Limitations and Future work

The study has limitations like any other research. The data was collected only from experts in selected Saudi universities. This may affect the generalization of the findings. Future work could also focus on collecting data from students to find out about the learning behaviour related to big data.

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