Big Data Analytics Evaluation, Selection and Adoption: A Developing Country Perspective

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Abstract
One of the biggest challenges for organizations especially in a developing country is to select the suitable big data analytics (BDA) platform that can satisfy their requirements. Trade-offs are exist among multiple business requirements fulfilled by different BDA platforms. This paper formulates the selection of BDA platforms as a fuzzy multi-criteria group decision making problem, and presents a fuzzy multi-criteria group decision making framework that helps organizations to evaluate, select, and adopt a suitable BDA platform that best satisfies their requirements. An Intuitionistic Fuzzy Goal Programming (IF_GP) algorithm based on goal programming and intuitionistic fuzzy numbers is developed to facilitate an agreement among a group of decision makers and eliminate the uncertainty to better represent their opinions. The developed algorithm is incorporated within the proposed framework for adequately dealing with the BDA platform performance evaluation and selection problem.
A numerical example for BDA platform selection is given to illustrate the application of proposed framework and IF_GP algorithm using a Jordanian case study. The need for this paper is important as the outcomes and conclusions of the analysis could be utilized to improve and hasten the adoption of using big data analytics technology in a developing country.
Key words:
Big data; Big data analytics (BDA), BDA platform, Goal programming, Intuitionistic fuzzy numbers; Multi- criteria group decision making; Adoption; Jordan.

1. Introduction

Across the globe, governments continuously collect, store and even share data about citizens, businesses, and other governmental units. Businesses are also doing the same with their customers, consumers and/or other businesses. Millions of people share and store texts, photos and videos every minute especially with the rapid proliferation of social networking sites such as Facebook, Twitter, WhatsApp and LinkedIn. Accordingly, immeasurable amount of data and information are generated and shared Worldwide (Agarwal and Dhar, 2014). Dobre and Xhafa (2014) reported that "every day the world produces around 2.5 quintillion bytes of data (i.e.1 Exabyte equals 1 quintillion bytes or 1 Exabyte equals 1 billion gigabytes)". Gantz and Reinsel (2013) predict that these data will be over 40 Zettabytes by 2020.

Accordingly, with that immeasurable increase of data worldwide, the ability to take advantage and create values from that mass data and information becomes a serious issue for organizational achievement (Olszak, 2016). Without a doubt, with this huge amount of compound and diverse data, big data phenomenon has dramatically emerged. Big data refers to "datasets that are both big and high in variety and velocity, which makes them difficult to handle using traditional tools and techniques" (Elgendy and Elragal, 2014). Yang et al. (2017) said that big data refers to the torrent of digital data (texts, geometries, images, videos, sounds and combinations of each) from various digital sources, include sensors, digitizers, scanners, mobile phones, Internet, e-mails and social networks. Thota et al. (2017) said that big data is information assets which have high volume, variety and velocity that requires an innovative cost effective of information processing that facilitate a better insight, process automation and decision making. Desouza and Smith (2014) define big data through its seven V's characteristics (Volume, Velocity, Variety, Viscosity, Variability, Veracity and Volatility). Others define big data from the processing view as the system that enhance the decision making and the insight discovery using an optimized processing for a high volume, high velocity, and/or high variety information (Gartner, 2012). Chen et al. (2013) indicated that big data is a huge dataset that can be manipulated by a common software tool to detain, control and process the data within an allowed time.

However, with the great development in the capacity, speed, and intelligence of storage and CPUs, organizations moved toward investment in big data collection and analysis instead of being unable to manage it (Russom, 2011). Advanced analytics is a collection of different tool

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types, including those based on predictive analytics, data mining, statistics, artificial intelligence, natural language processing that can be combined with big data to discover new and unique knowledge and facts that are important and highly required for organizational (Russom, 2011). Using and applying advanced analytics to analyze the big data sets, organizations can understand the current state of the business and track still-evolving aspects such as customer behavior (Özsu and Valduriez, 2011). Combining big data for massive amounts of detailed information together with advanced analytics yields big data analytics (BDA) as a new modern aspect in business intelligence nowadays (Russom, 2011).

BDA is a holistic approach and system to manage, process and analyze huge amount of data in order to create value by providing a useful information from hidden patterns to measuring performance and increase competitive advantages (Wamba et al., 2017; Wamba et al., 2015; Elgendy & Elragal, 2014; Holsapple et al., 2014). BDA can also be technologies that are concerned with how to create insightful trends in business intelligence (Chen et al., 2012; Russom, 2011). Gupta and Chaudhari (2015) believed that the future can be predicted by analyzing big data which is classified as an important factor to society and business.

Chen et al. (2014) present a review for big data and the correlated technologies such as cloud computing, data centers and Apache Hadoop. Elgendy and Elragal (2014) study various big data analytical tools and its applications in decision making area to reveal the hidden insights and valuable knowledge using suitable analytical methods. Vossen (2014) discussed the importance of business intelligence as one of the techniques and applications of big data and its analytics. Loshin (2013) argued that the fitness of business would be evaluated by a combination of various factors such as (feasibility, reasonability, value, integrability and sustainability) when attempt to properly deal with big data issue. Chen et al. (2014) presented and evaluated a framework regarding processing and managing big data. Singh and Reddy (2014) presented diverse platforms with their benefits and drawbacks based on factors such as “scalability, data I/O rate, fault tolerance, real-time processing, data size supported and iterative task support”.

Due to its benefits and advantages in different life aspects, many researchers propose the big data and its tools as a fourth paradigm of sciences (Strawn, 2012, p.34) or the new paradigm of knowledge (Hagstrom, 2012, p. 2) or even the next edge for innovation (Manyika et al., 2011, p.1). Yiu (2012) states that organizations gain a competitive advantage and improved organizational performance due to using the tools and technologies for analyzing their big data. BDA also helps organizations strengthen customer relationship management, enlightening the management of their operations and the operational efficiency risk which has a big impact in their performance (Kiron, 2013). BDA is predicted to have remarkable effects inside an assortment of industries such as main retail organizations which are currently forcing big data abilities to develop the customer knowledge, and decrease fraud (Tweney, 2013). BDA is predicted to cut the cost of operation and enhance the life quality in the healthcare area (Liu, 2014). Moreover, Davenport et al. (2012) and Wilkins (2013) mention that BDA play a role in strength business process monitoring in manufacturing and operation management, as well as in supplying chain visibility to help in improving manufacturing and industrial automation. The high operational and strategic potential of BDA give it a major role to enable an enhanced business efficiency and effectiveness.

The literature on BDA has acknowledged an affirmative bond among the employment of customer analytics and organization performance (Germann et al., 2014). For instance, BDA permits companies to analyze and accomplish strategic plans over data lens (Brands, 2014). Hagel (2015) stated that BDA now is an essential element for business process decision making. Liu, (2014) argues that BDA is a good indicator for the organization performance. Wills (2014) explained how Amazon.com uses BDA to target their customers and that 35% of purchases made are due to tailored purchase suggestion to customers based on BDA. According to the study in (Chen et al., 2014), several important advantages for business can be attained when adopting and using big data and analytics such as increasing operational efficiency, informing strategic direction, developing better customer service, identifying and developing new products and services, identifying new customers and markets.

BDA is listed in the ‘‘top 10 critical tech trends for the next five years’’ and “top 10 strategic technology trends for 2013” (Savitz, 2012). BDA technologies and services are predicted to grow from $6 billion in 2011 to $23.8 billion in 2016 (Vesset et al., 2012). This increase represents a compounded annual growth rate of 31.7% or about seven times that of the overall information technology market. BDA implementation is included in the top ten business priorities list obtained from a global survey by Gartner on business strategies, priorities and plans. This makes BDA a strategic option for organizations to harness the data produced by the digital technologies and creates insights for future strategies. In turn, these insights could be used for better decision making which could help the organizations gain a competitive edge. Consequently, it is necessary to understand the usage and adoption of BDA in developing countries and their economies (Verma et al., 2017).

Several well-known BDA platforms with various features, capabilities, tools are exist and adopted by common organizations (Saecker and Markl, 2013). We think that matching BDA platform capabilities and an organizational needs is a key for organizations to attain more values and advantages from big data. Thus, choosing effectively the right BDA platform that best satisfies organizational requirements is a challenging issue and will be handled in this paper. The availability of many BDA services makes it difficult for the organizations to choose the service that will be best suited for their needs. Indeed, it became a defy situation as many factors play major roles when selecting the best suitable analysis service. For example, each BDA alternative might offer similar services at different performance levels with different sets of features and capabilities. While one BDA satisfies one business requirement, it may not satisfy other business requirements, and if one BDA satisfies one business requirement the other DBA platforms may not satisfy that business requirement (Husain, 2016 b). Undoubtedly, with the diversity of BDA platforms, organizations deal with a challenging process to discover and select the suitable BDA platform that can satisfy their requirements. Trade-offs are exist among multiple business requirements fulfilled by different BDA platforms. Indeed, it is not sufficient to just discover multiple BDA platforms, but it is important to determine the most suitable one through an effective performance evaluation for a specific manner (Husain, 2014).

Evaluating the performance of the available BDA platforms with respect to the multiple conflicting criteria is considered a complex and challenging multi-dimensional decision making problem. The challenge relays in the availability of multiple BDA platforms with contradicting characteristics; multiple and conflicting evaluation criteria with incomplete or unknown weightings; multiple decision makers with their different requirements; and presence of imprecise and subjective judgments as fuzzy data about the performance of the alternatives. To adequately handle such a problem, an overall evaluation of each BDA is required.

To the best of our knowledge, there is little of research that aims to help business organizations for selecting the most fitting BDA platform. Selecting suitable big data visualization tool has been addressed by a study in Hassan and Elragal (2017). A more generalized research that is interested in BDA platforms evaluation and helps organizations choose the right one using AHP method is presented in (Lněnička, 2015). However, previous approaches cannot accommodate the intended problem situation and requirements in this paper. Firstly; there is an immense need to achieve better agreement and facilitate the acceptance of the decision among the group of decision makers. Additionally, achieving a better representation for subjective assessment and enabling decision makers to judge and express their opinions with less present knowledge about alternatives are important aspects to be supported and considered to facilitate the problem complexity.

To better handle such issues, evaluating the performance of the available BDA platforms with respect to multiple and conflicting criteria is formulated as a fuzzy multi-criteria group decision making problem. a fuzzy multi-criteria group decision making framework that helps organizations to evaluate, select, and adopt a suitable BDA platform that best satisfies their requirements is presented. Intuitionistic fuzzy numbers (Atanassov, 1998; Atanassov, 1999) are used to better model the subjectivity and imprecision of decision maker judgments and opinions. An effective algorithm is developed based on a goal programming model with intuitionistic fuzzy numbers to adequately deal with the multiple conflicting criteria and decision makers of the problem. An example is presented to demonstrate the applicability of the proposed fuzzy multi-criteria group decision making method for solving the multi-criteria group decision making problem in real situations. This research study aims at achieving the following objectives: firstly, to investigating and finding evaluation criteria that best reflect the organizational requirements and needs to be reference for BDA performance evaluation. Secondly, enabling organizations to evaluate, select, and adopt a suitable BDA platform that best achieves their requirements and attains higher values from big data. Additionally, ensures that all interests and perceptions of decision makers will be considered in a robust and efficient performance evaluation process. Finally, enabling decision makers to express their opinions and assessments with less knowledge about BDA alternatives.

The rest of this paper is organized as follows. In Section 2, a description of fuzzy multi-criteria group decision making framework for BDA platform evaluation and selection is presented. A detailed description of the evaluation criteria, BDA evaluation process is presented in Section 3 and 4. Section 5 presents a detailed description of IF_GP algorithm for agreement process. The 6th section gives a numerical example as a case study of BDA platform selection and evaluation by applying steps of the proposed framework. Finally, a conclusion of this paper is presented in the last section.

2. The BDA Evaluation, Selection, and Adoption

Despite the challenges and barriers of BDA adoption, and the difficulties the firms might face in proving the value of big data investments (Wikibon, 2015; Hanchard &

Ramdas, 2014), it becomes a necessary requirement for organizations to use and adopt BDA (Verma et al., 2017) Businesses are facing challenges in the management and capitalization of data with the significant increase in its amount and sources to gain advantages. Thus, the demand for a new class of technologies and analytical methods has increased (Gandomi and Haider, 2015). BDA has emerged as a method to manage and analyze such data (Ularu et al., 2012; Verma et al., 2017) and help take advantages of all available information such as enhancing decision making, help organizational success, and remain being competitive (Al-Hujran et al., 2015).

However, due to the complexity of the selection decision of the best BDA platform that can fulfill organizational requirements and maximize the potential benefits of all available information, and given the diversity of BDA platforms, the proposed solution is to build a framework that supports organizations and helps their decision makers to evaluate set of BDA platforms and select the suitable one that best achieves their requirements and needs. The proposed fuzzy multi-criteria group decision making framework steps are shown in figure 1 and includes (a)problem definition, (b)performance evaluation, (c)aggregation, and (d)ranking and selection.

Problem definition stage includes identifying the problem requirements such as participant decision makers and their weights, defining the potential BDA platforms (alternatives), defining the relevant evaluation criteria and with their weights. Identifying the alternatives for the BDA platform selection problem is to find out the most appropriate set of BDA platform alternatives among the others. This can be done during a survey of the existing DBA platforms and recommends the best set of platforms based on users' ratings or popularity of use. Accordingly, evaluation criteria that best represent points of interest for BDA users that might reflect their requirements and needs must be identified and used as bases for the evaluation. The criteria and alternatives must be carefully determined in the decision making process because it is directly related to the ability of the organizations in achieving and sustaining its competitiveness and effectiveness.

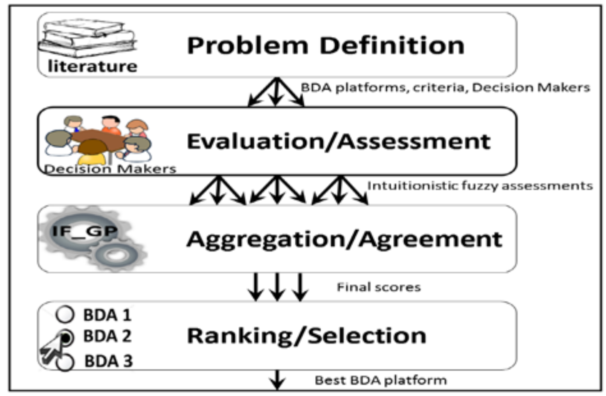

Fig. 1 Fuzzy multi-criteria group decision making framework for BDA evaluation, selection, and adoption

The performance evaluation step is to enable decision makers to specify and express their opinions and assess the ability of each alternative in satisfying the criteria. In this phase, each decision maker will rate the ability of each alternative in satisfying each evaluation criterion as an intuitionistic fuzzy numbers. The assessments and judgments of the decision makers need to be aggregate as collective opinions, and the collective opinions about several criteria also need to be aggregated into overall assessments. IF_GP model is constructed to perform the two-phase aggregation; opinions of decision makers aggregation as collective opinions, and criteria aggregation as final scores. Finally, based on the calculated final scores, all available alternatives can be ranked and the most appropriate one can be selected. The most appropriate alternative is the alternative that best satisfies the group of decision makers' requirements. The process of evaluation, selection and adoption of BDA platforms can be summarized in the following steps presented in Table 1.

Table1: Steps to evaluate, select and adopt of BDA platforms

Steps	Actions
Problem definition	Identify the problem requirements such as the participant decision makers and their weights.
	Define the potential BDA platforms (alternatives).
	Define the relevant evaluation criteria.
	Obtain the weights of the evaluation criteria.
Evaluation	Obtain the intuitionistic fuzzy assessments of each alternative with respect to each criterion from each decision maker.
Aggregation/ agreement	Decision maker aggregation: Construct aggregated intuitionistic fuzzy assessments about each alternative with respect to each criterion by all decision makers.
	Criteria aggregation: Construct aggregated final scores for alternatives with respect to all criteria by all decision makers.
Ranking and selection	Rank the alternatives based on the obtained scores and select the best one.

3. BDA Evaluation Criteria

To ensure accuracy and effectiveness of the evaluation and selection process, it is important to define a set of evaluation criteria that best reflects the desired BDA characteristics that represent interest points and requirements for organizations and BDA users. The criteria must be carefully determined in the decision making process because it directly related the ability of the organizations in achieving and sustaining its competitiveness. So that, several researches that highlighted BDA attributes, trends, and options have been investigated in this paper to identify the most important criteria for performance evaluation of BDA platforms. A review of the related literature leads to the classification of the evaluation criteria into (a)Advanced analytics, (b)Integrated and embedded, (c)Data scalability and flexibility, (d)Data security and privacy, (e)Perceived usefulness, and (f)Perceived ease of use.

Advanced analytics (C1) criterion represents the ability of BDA platform to offer and support users a wide variety of advanced analytical techniques, algorithms, and models to help capture, curate, analyze and visualize big data and support for analytics (Özsu and Valduriez, 2011). Nowadays moving into advanced analytics is an important trend in business intelligence (Russom, 2011). However, many people are involved in BDA for different purposes. For example, describing marketers, consultants, statisticians, data governors and risk managers are involved in design and execution of analytics, engineers and researchers are using the analytics, and business professionals are doing the analytics (Russom, 2011). Hence, a BDA needs to provide a wide variety of advanced analytical techniques, algorithms, and models that can support the vast requirements for such variant users from different disciplines. Limited tools and methods provided through BDA limit the uses of big data which may prevent organizations to discover new facts and knowledge. BDA that supports an advanced multidisciplinary methods and tools are recommended and preferred for business to discover the valuable information from big data that meets a variety of needs (Chen et al., 2014).

Integrated and embedded (C2) refers to the degree to which a BDA tools can integrate with other existing technologies, and to run on various big data platforms. Organizations normally have heterogeneous environments in terms of hardware, platforms, software tools, and data due to the complexity and expansion of the number of technologies. Such existing environmental variables need to be considered when developing a new technology rather to be discarded or replaced. Big data in large and well-established business environments should not be separate, but must be embedded and integrated with the existing environment. Analytics on big data have to coexist with analytics on other existing types of technologies and data. For example, Hadoop clusters have to do their work alongside with IBM mainframes, data scientists must somehow get along and work jointly with mere quantitative analysts (Davenport and Dyché, 2013). Indeed, new BDA needs to integrate with the old existing environmental variables, and embedded operational and decision processes. Big data cannot be solved effectively without an ability to integrate with other existing technologies and big data tools in the environment. In sum, the ability of the analytical tools to run on various big data platforms, integrate with other technologies and embed their analytics into systems and processes attract decision makers to adopt and use that analytics.

Data Scalability and flexibility (C3) represents the degree to which a BDA platform can be adapted to use structured and unstructured data from multiple sources and its capability of scaling the increasing amount of data. Organizations are increasingly adding large volumes of structured and unstructured data from various sources in order to yield new perceptions and opportunities (Russom, 2011). The volume of data, the number of data sources, and the difference in the format are often incremental, rather than an advance in capability. Hence, the ability of BDA platform to handle a growing amount of data- especially unstructured data- is challenging and presents an important requirement for organizations. The BDA that is more capable to handle growing data and can be enlarged easily, represents a better DBA choice (Lněnička, 2015).

Data Security and Privacy (C4) represents the degree to which data security approaches are developed and employed in a BDA environment. BDA platform needs to provide security tools and control procedures for errors, malfunctions, improper use (Marakas and O'Brien, 2013). Due to massive data volume that distributed over its networks (Agrawal et al., 2008), data security is considered one of the key challenges to adopt and even accept BDA (Soon et al., 2016). Data security protection, intellectual property protection, personal privacy protection, commercial secrets and financial information protection are significant security problems that need to be controlled (Matthew et al., 2012). Indeed, several data management professionals cited such data security concerns as significant barriers to big data adoption (Davenport and Dyché, 2013).

According to Lee (2017) “weak security creates user resistance to the adoption of big data. It also leads to financial loss and damage to a firm’s reputation”. He also pointed that “as big data technologies mature, the extensive collection of personal data raises serious concerns for individuals, firms, and governments. Without addressing these concerns, individuals may find data analytics worrisome and decide not to contribute personal data that can be analyzed later."

Previous studies have found that security and privacy are important determining factors in adoption process of big data (Bertino and Ferrari, 2018; Bertino and Kantarcioglu, 2014; Cuzzocrea, 2014; Lee, 2017; Matturdi et al. 2014) and in technology adoption (Barker et al., 2005; Kambourakis, 2013; Du et al., 2012). Due to their ability to predict an intention to adopt a subsequent use for a given technology, data security and privacy have been proposed as one evaluation criterion. The aim is to find and select a BDA platform that develops and employs powerful security approaches and tools. The highest level of security implemented in BDA platform is important to encourage users to adopt and select BDA platform.

Perceived usefulness (C5) refers to the ability of BDA platform and its related tools to enhance decision making process, help organizational success, and remain being competitive when it is used by business organizations, and its ability to improve and enhance the performance and effectiveness of their business processes and tasks (Al-Hujran et al., 2015). This factor is derived from the Technology Acceptance Model (TAM) theory which was found by Davis (1989). Perceived usefulness is defined by Davis (1989, p.320) as "the degree to which a person believes that using a particular system would enhance his or her job performance". Accordingly, if individuals believe that the system will enhance their job performance and effectiveness they will adopt and use the new system. The usage behavior of an emerging information technologies has corroborated that perceived usefulness and ease of use have classified as the strongest predictors of behavioral intention (Venkatesh et al. 2003, 2012). Perceived usefulness has been chosen due to their ability to predict an individual's intention to adopt a subsequent use for a given technology. It has been found as an important determining factor in the adoption of big data (Aloysius et al. 2016; Soon et al., 2016), and in the adoption and acceptance of new technology (Chong, 2013; Faqih and Jaradat, 2015; Jaradat and Faqih 2014; Lai and Lai, 2013; Venkatesh and Davis, 2000; Venkatesh & Bala, 2008). However, some studies did not find any significant effect of perceived usefulness (Carter and Bélanger, 2005).

Perceived ease of use (C6) refers to the simplicity and the ease of usage, installation, and maintenance of a BDA platform and its tools, skills and knowledge needed for deploying new technologies (Lněnička, 2015). This factor is derived from the TAM theory. Perceived ease of use is defined by Davis (1989, p.320) as "the degree to which a person believes that using a particular system would be free of effort". Perceived ease of use has been chosen due to their ability to predict an individual's intention to adopt a subsequent use for a given technology. There are several studies that found that the perceived ease of use is a predictor for new technology adoption and acceptance (Aloysius et al. 2016; Venkatesh and Davis, 2000; Esteves and Curto, 2013; Chang et al., 2015; Rajan & Baral, 2015). However, Soon et al. (2016) did not find any significant effect of perceived ease of use in the adoption of big data. In addition, some researchers have not demonstrated that perceived ease of use as an important determining factor in the adoption of new technology (Ahmed and Campbell, 2015; Low et al., 2011; Shih and Huang, 2009; Lederer et al., 2000)". We believe that perceived ease of use is an important requirement for organizations to be satisfied by a selected BDA platform. Table 2 presents a summary of the proposed BDA evaluation criteria.

Table 2: BDA evaluation criteria

Criterion	***Description***
Advanced analytics	Ability of BDA platform to offer users a wide variety of advanced analytical techniques, algorithms, and models.
Integrated and embedded	Ability of BDA platform and its tools to integrate with other existing technologies, and to embed their analytics into systems and processes, and its ability to run on big data platforms.
Data scalability and flexibility	Degree to which a BDA platform can be adapted to use structured and unstructured data from multiple sources and its capability of scaling the increasing amount of data.
Data security and privacy	The degree to which data security approaches are developed and employed in the BDA environment.
Perceived usefulness	Ability of BDA platform and its related tools to enhance decision making process, help organizational success, and remain competitive when it is used by business organizations, and its ability to improve and enhance the performance and effectiveness of their business processes and tasks.
Perceived ease of use	Simplicity and the easiness of usage, installation, and maintenance of a BDA platform and its tools, skills and knowledge needed for the deploying new technologies.

4. BDA Platform Assessment and Evaluation

The key idea in this phase is to enable decision makers to specify and express their opinions and assess the ability of each BDA platform alternative in satisfying the evaluation criteria as intuitionistic fuzzy numbers (Atanassov, 1998; Atanassov, 1999). Intuitionistic fuzzy numbers are adopted to better model the subjectivity and imprecision of the human decisions, and support for simultaneous contradicting assessments. Intuitionist fuzzy numbers are characterized and distinguished by a membership and a non-membership function over ordinary fuzzy set (Zadeh, 1965) whose basic component is only a membership function. The performance of the alternative (i) with respect to each criterion (j) can be measured and expressed by decision maker (k) as an intuitionistic fuzzy number (R_{ij}^k) (Atanassov, 1999; Xu, Z. S., 2007). Intuitionistic fuzzy value $R_{ij}^k = (\mu_{ij}^k, v_{ij}^k)$ consists of the certainty degree μ_{ij}^k which represents the ability of the alternative i to satisfy the criterion j (membership function) and the uncertainty degree v_{ij}^k which represents the degree that of the alternative i does not satisfy the criterion j (none membership function) from the point of view of decision maker k (Yue, 2014).

Intuitionistic fuzzy numbers are adopted because their ability to deal with fuzziness, uncertainty, and subjective opinions of the decision makers effectively. Using intervals to express subjective assessment values requires less knowledge from decision makers (Wibowo and Deng, 2015). Intuitionistic fuzzy numbers also enable experts to judge and agree upon certainty and uncertainty assessment simultaneously, which can be efficiently aggregated (Yue, 2014; Tan and Deng, 2010; Yuan et al., 2014). Indeed, many real situations require defining membership and a non-membership values by a group of decision makers. For instance, if one decision maker organizes and sets a group of experts to evaluate a set of alternatives (ten experts for example), four of them consider an alternative strong in achieving a specific criterion, three experts consider an alternative low in achieving that criterion, others do not judge at all, then, the performance of such alternative can be expressed as an intuitionistic fuzzy value (0.4,0.3) (Su et al. 2012).

The performance evaluation of BDA platforms is performed by decision makers through the determination of the performance rating of each platform alternative with respect to each criterion by individual decision maker as (R_{ij}^k) values where $R_{ij}^k = (\mu_{ij}^k, v_{ij}^k)$, $0 \le \mu_{ij}^k + v_{ij}^k \le 1$, $\mu_{ij}^k = v_{ij}^k$, $v_{ij}^k = \mu_{ij}^k, = 0.5$. As a result, the intuitionistic fuzzy performance rating values for the multi-criteria group decision making problem for each decision maker can be expressed as:

$$R_{ij}^k = \begin{bmatrix} \mu_{1,1}^k, v_{1,1}^k & \mu_{1,2}^k, v_{1,2}^k & \ldots & \mu_{1,m}^k, v_{1,m}^k \\ \mu_{2,1}^k, v_{2,1}^k & \mu_{2,2}^k, v_{2,2}^k & \ldots & \mu_{2,m}^k, v_{2,m}^k \\ \ldots & \ldots & \ldots & \ldots \\ \mu_{n,1}^k, v_{n,1}^k & \mu_{n,2}^k, v_{n,2}^k & \ldots & \mu_{n,m}^k, v_{n,m}^k \end{bmatrix}$$

5. IF_GP Group Decision Making Aggregation/Agreement

The performance evaluation and selection of BDA platforms is modelled as a fuzzy multi-criteria group decision making problem where A = {A1, A2,...,An} is the set of n alternatives, C = {C 1, C2, ..., Cm} be the set of m criteria with weight vector wc = {wc1, wc2 ,. . ., wcm}, D = {D1, D2, ..., Ds } be the set of s decision makers with weight vector wD = {wD1, wD2 ,. . ., wDs}, here $\sum_{k=1}^{s} w_{Di} = 1 \; and \sum_{j=1}^{m} w_{cj} = 1$. Performance evaluation and selection of BDA platforms with respect to multiple and conflicting criteria are considered a complex and challenging multi-dimensional decision making problem. This is due to the availability of multiple BDA platforms with contradicting characteristics; multiple and conflicting evaluation criteria with incomplete or unknown weightings; multiple decision makers with their different requirements; and the presence of imprecise and subjective judgments as a fuzzy data about the performance of the alternatives. Indeed, if one BDA platform suits one organization, it may not suit the other organizations, and if one BDA platform suits one organization from one perspective it may not suit the other perspectives (Husain, 2016 a). To solve such a problem and handle such issues, this paper presents a fuzzy multi-criteria group decision making method based on the linear goal programming and intuitionistic fuzzy numbers.

Owing to its vast applicability in multi objective decision scenarios, goal programming has been adopted and formulated in this paper to perform the two phase aggregate; decision makers aggregation and criteria aggregation. Decision makers aggregation operator shown in figure 2(a) can be applied to aggregate intuitionistic fuzzy rating values (R_{ij}^k) of each decision maker and construct aggregated decision makers assessments (R_{ij}) which represents collective opinions of all decision makers about each alternative with respect to each criterion in a form of intuitionistic fuzzy value. Criteria aggregation operator shown in figure 2(b) can be applied to aggregate the collective intuitionistic fuzzy assessments about each criterion into final score values (R_i) which represents the overall performance of each alternative with respect to all criteria from the all decision makers.

Several aggregation operators for aggregating intuitionistic fuzzy numbers have been proposed (Xu, 2007; Yager and Filev, 1999). Intuitionistic fuzzy ordered weighted averaging (IFOWA) operator (Xu, 2007), the generalized intuitionistic fuzzy ordered weighted averaging (GIFOWA) operator (Li, 2010), and the induced generalized intuitionistic ordered weighted averaging (I-GIFOWA) operator Su et al. (2012) are common widely used operators that are extended from each other which are based on ordered weighted averaging (OWA) operator (Yager, 1988; Yager and Filev (1999). For example, Wibowo and Deng (2013) adopt I-GIFOWA operator as a part in the solution and introduce an intuitionistic fuzzy weighted average (IFWA) operator for aggregating the intuitionistic fuzzy decision.

However, goal programming is characterized and distinguished by minimizing deviations from an anticipated set of goals over such ordinary aggregation operators (Trivedi and Singh, 2017). Goal programming is adopted to accommodate the situation in this paper where there is an immense need to facilitate the acceptance of the decision. Indeed, goal programming attempts to find a collective opinion that minimizes deviations from the opinions of each individual decision maker. Hence, it achieves better agreement and facilitates the acceptance of the decision among the group. Although goal programming approach and its variants have been used under similar situations in various fields (Husain, 2013; Husain, 2016), to the best of our knowledge this is the first approach to use multi-criteria approach applied to aggregate intuitionistic fuzzy numbers to select best BDA platform.

$$\textbf{Minimize} \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{s} \mu\_over_{ij}^{k} + \mu\_under_{ij}^{k} + v\_over_{ij}^{k} + v\_under_{ij}^{k}$$

Where

For *i=1… n*

For *j=1 … m*

For *k=1 … s*

$$\mu_{ij} - \mu\_over_{ij}^{k} + \mu\_under_{ij}^{k} = \mu_{ij}^{k} * wd_k$$
$$v_{ij} - v\_over_{ij}^{k} + v\_under_{ij}^{k} = v_{ij}^{k} * wd_k$$

For *i=1… n*

For *j=1 … m*

$$\mu_{ij} + v_{ij} \le 1, \quad 0 \le \mu_{ij} \le 1, \quad 0 \le v_{ij} \le 1$$

(a) Decision Makers aggregation operator

$$\textbf{Minimize} \sum_{i=1}^{n}\sum_{j=1}^{m} over_{ij} + under_{ij}$$

Where

For *i=1… n*

For *j=1 … m*

$$A_i - over_{ij} + under_{ij} = (\mu_{ij} - v_{ij}) * wc_j$$

For i=1 … n

$$-1 \le A_i \le 1$$

(b) Criteria aggregation operator

Fig. 2 The proposed IF_GP algorithm (a) Decision makers aggregation operator (b) Criteria aggregation operator.

Where n, m, and s are the numbers of alternatives, criteria, and decision makers consequently. μ_{ij}^{k}, v_{ij}^{k} represent intuitionistic fuzzy assessments by decision makers which are inputs of criteria aggregation operator. wd_k, wc_j are the weights of decision makers and evaluation criteria. μ_{ij}, v_{ij} are intuitionistic fuzzy decision variables which are the intended output for decision makers aggregation operator and are the inputs of criteria aggregation operator. A_i are decision variables which are the intended output for criteria aggregation operator. Higher final score value A_i represents better performance for BDA alternative.

The proposed goal programming model is constructed and formulated in such a way that satisfies the BDA platform selection problem requirements and variables. To achieve higher efficient and reliable results, score function (S) of an intuitionistic fuzzy value (Chen and Tan, 1994) has been used in the formulation of the proposed goal programming aggregation operators due to its simplicity and computation efficiency (Wibowo and Deng, 2013). Score function S is a popular function to determine the scores of the overall intuitionistic fuzzy numbers which can be represented as $S = (\mu_{ij} - v_{ij})$ where $S \in [-1,1]$.

6. Case Study

The value that can be derived from BDA differs from what traditional data analytics can offer. Therefore, combining large amount of collected data in order to be analyzed become an important organizational requirement. Organizations in Jordan- like other organizations in the world- are willing to create values from big data and analysis in order to take advantage of all available information and enhance decision making process, help organizational success, and remain being competitive (Al-Hujran, 2015; Chen, and Zhang, 2014). Indeed, it's realized from the related literature that there is an immense need to adopt and use BDA to help in tapping into complex streams of datasets and attain such values. The decision is therefore taken to select the most suitable BDA platform.

In order to select DBA platform that best satisfies the entire organizational requirements and functions, and can help improve various organizational business processes, selection decision should be made with participation of a cross-functional group of decision makers that represents different levels and services of the company. A decision committee consisting of three managers for three different departments is formed as decision makers D1, D2 and D3 whose weight vector is w= (0.20, 0.33, 0.47). In this evaluation process, each manager with the help of underlying department members will investigate, analyze and finally assess the available and commonly adopted options of BDA platforms that might help meet their requirements and goals, and come-up with an assessment that represents an opinion of that decision maker.

Four potential DBA platform alternatives have been identified and recommended namely: (a) 1010data, (b) Amazon Redshift, (c) Cloudera, and (d) HP Vertica.

Accordingly, six evaluation criteria are determined to be used as bases for performance evaluation of BDA alternatives including advanced analytics(C1), integrated and embedded(C2), data scalability and flexibility(C3), data security and privacy(C4), perceived usefulness(C5), perceived ease of use(C6) with weight vector is w=(0.08, 0.22, 0.18, 0.10, 0.14, 0.28). The proposed fuzzy multi-criteria decision making goal programming framework is used to evaluate the performance of BDA alternatives based on such criteria and help select the best one. Figure 3 shows the hierarchical structure of the BDA platforms performance evaluation, selection, and adoption.

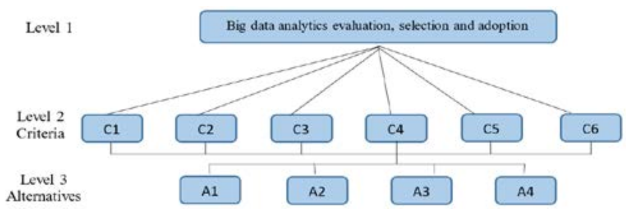

Fig 3: Hierarchical structure of BDA evaluation, selection, and adoption.

The evaluation and selection process has started by asking each individual decision makers (manager) to provide the intuitionistic fuzzy assessments of each alternative with respect to each criterion in a form of an intuitionistic fuzzy numbers. Each decision maker manager organized meetings with their expert department members in order to judge the degree that each alternative can or cannot satisfy each criterion. The relative performance of all available BDA alternatives in regard to all decision makers is determined and provided by the decision makers as shown in Table 3. Each intuitionistic fuzzy number represents a judgment obtained from a set of expert members of a department for each decision maker manager about each alternative whether strongly satisfies each criterion or not.

Table3: Intuitionistic fuzzy performance assessments of BDA platforms by decision makers

		C1	**C2**	**C3**	**C4**	**C5**	**C6**
A1	D1	(0.2,0.7)	(0.4,0.6)	(0.3,0.7)	(0.5,0.5)	(0.4,0.3)	(0.6,0.2)
	D2	(0.4,0.6)	(0.5,0.3)	(0.4,0.5)	(0.1,0.9)	(0.6,0.3)	(0.2,0.7)
	D3	(0.7,0.2)	(0.4,0.2)	(0.8,0.2)	(0.5,0.4)	(0.5,0.5)	(0.6,0.3)
A2	D1	(0.7,0.3)	(0.8,0.1)	(0.6,0.2)	(0.6,0.1)	(0.1,0.5)	(0.4,0.6)
	D2	(0.2,0.8)	(0.3,0.4)	(0.2,0.8)	(0.9,0.1)	(0.2,0.7)	(0.1,0.7)
	D3	(0.4,0.6)	(0.1,0.5)	(0.5,0.4)	(0.1,0.5)	(0.6,0.2)	(0.3,0.2)
A3	D1	(0.9,0.1)	(0.2,0.8)	(0.6,0.1)	(0.4,0.5)	(0.1,0.5)	(0.2,0.7)
	D2	(0.6,0.3)	(0.9,0.1)	(0.2,0.7)	(0.5,0.5)	(0.3,0.7)	(0.8,0.2)
	D3	(0.1,0.9)	(0.4,0.5)	(0.5,0.5)	(0.2,0.7)	(0.1,0.5)	(0.4,0.6)
A4	D1	(0.8,0.2)	(0.5,0.5)	(0.3,0.4)	(0.1,0.9)	(0.4,0.6)	(0.6,0.2)
	D2	(0.6,0.2)	(0.4,0.5)	(0.5,0.5)	(0.9,0.1)	(0.3,0.4)	(0.3,0.2)
	D3	(0.4,0.5)	(0.8,0.2)	(0.4,0.6)	(0.4,0.6)	(0.7,0.3)	(0.1,0.9)

Table 4: Collective intuitionistic fuzzy assessments that represent all decision makers

	C1	**C2**	**C3**	**C4**	**C5**	**C6**
A1	(0.132,0.14)	(0.165,0.099)	(0.132,0.14)	(0.1,0.188)	(0.198,0.099)	(0.12,0.141)
A2	(0.14,0.264)	(0.099,0.132)	(0.12,0.188)	(0.12,0.033)	(0.066,0.1)	(0.08,0.12)
A3	(0.18,0.099)	(0.188,0.16)	(0.12,0.231)	(0.094,0.165)	(0.047,0.231)	(0.188,0.14)
A4	(0.188,0.066)	(0.132,0.1)	(0.165,0.165)	(0.188,0.18)	(0.099,0.132)	(0.099,0.066)

The proposed IF_GP is applied to perform the decision makers' aggregation using the obtained intuitionistic fuzzy performance rating values of decision makers along with their weights. The results are collective intuitionistic fuzzy numbers as denoted in Table 4 that represent the output of decision makers aggregation, and used as input for criteria aggregation together with criteria weights. The final scores for the BDA alternatives are produced using criteria aggregation operator. Table 5 shows the overall performance of BDA alternatives and their corresponding rankings. Indeed, alternative 4 (HP Vertica) has the best performance, relative to other alternatives as it has the highest overall performance value.

Table 5: Final scores and ranking of BDA platforms

BDA platforms(Alternatives)	***Score***	***Rank***
A1: 1010data	-0.00064	3
A2: Amazon Redshift	-0.00992	4
A3: Cloudera	0.00616	2
A4: HP Vertica	0.00704	1

The results above show that the proposed multi-criteria group decision making approach is effective for handling the multidimensional nature of the evaluation process. Indeed, all of the provided opinions and perceptions of decision makers, the positive or negative ones, are considered and aggregated into final scores. Each final score represents the closest value that has minimum deviation to all positive assessments of decision makers and vice versa about the negative assessments considering their weights in order to achieve better agreement upon the selected BDA platform. Additionally, each decision maker expresses his/her own certain and uncertain fuzzy assessment and judgment simultaneously. Based on the identified criteria, BDA alternatives are comprehensively evaluated and their overall performance were determined which lead to the selection of the most appropriate BDA platform for the intended organization. Organization hopes to maximize the benefits and attain more advantages of the big data by adopting HP Vertica analytics platform.

7. Conclusion

Performance evaluation of several potential BDA platforms is a complex, challenging, and multi-dimensional process. Thus, a fuzzy multi-criteria group decision making framework that helps organizations to evaluate, select, and adopt a suitable BDA platform that best satisfies their requirements and attain higher values from big data is presented. An algorithm based on goal programming and intuitionistic fuzzy numbers is developed to facilitate an agreement that considers the all perceptions of decision makers and eliminate the uncertainty to better represent their opinions. The developed algorithm is incorporated within the proposed framework for adequately dealing with the multi-dimensional BDA platform evaluation and selection problem. With the use of an example, the proposed solution has demonstrated a number of advantages for effectively dealing with the problem of evaluating, selecting, and adopting of BDA platforms. Addressing a set of evaluation criteria that best reflects the organizational needs when selecting and adopting a BDA platform, enabling organizations to evaluate, select, and adopt a suitable BDA platform that best attains higher values from big data, ensures that all interests and perceptions of decision makers will be considered in the evaluation and selection process, and enabling decision makers to express their opinions and assessments with less knowledge about BDA alternatives. The proposed framework is found to be effective and efficient due to the comprehensibility of its underlying concepts and the straightforward computation process.

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