A Multi-Criteria Group Decision Making Method for Selecting Big Data Visualization Tools

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***Abstract*—Big data visualization tools are providing opportunities for businesses to strengthen decision making and achieve competitive advantages. Evaluating and selecting the most suitable big data visualization tool is however challenging. To effectively deal with this issue, this paper presents a multi-criteria group decision making method for evaluating and selecting of big data visualization tools. Intuitionistic fuzzy numbers are used to tackle the subjectiveness and imprecision of the decision making process. The concept based on ideal solutions is applied for producing a relative closeness coefficient value for every big data visualization tool alternative across all evaluation criteria. A big data visualization tool selection problem is presented to demonstrate the applicability of the method.**

***Index Terms*—Big Data Visualization Tool; Evaluation and Selection; Decision Makers; Subjectiveness; Imprecision.**

I. Introduction

Big data is defined as a large collection of multifaceted data sets, which can also be described as being high volume, variety and velocity, making difficult to move and process instantly with the traditional database management systems [1-3]. Businesses are finding it difficult to continue with traditional reporting process due to huge accumulation of data and not being able to use it in real-time to seize the actual potential of big data. A survey of IT managers reveal that more than 30% of the businesses receive more than 500 Terra bytes of data, which is not analyzed due to existence of mostly unstructured data [4]. Analyzing this can reveal hidden patterns, improve decision making process and enhance operational efficiency in organizations [5, 6]. The exploration of data discovery tools is considered worthwhile as they provide in-depth understanding and allow businesses to make informed decisions [6].

Gartner predicts that the adoption of big data visualization tools by organizations will increase by 30 percent annually through 2015 [7]. This is due to the capabilities of big data visualization tools to (a) perform real-time monitoring and forecasting of events, (b) provide timely insights from the organizational data, and (c) enhance decision making process [2, 7].

There are several data visualizations tools available in the market to analyze high volumes of data [8]. In fact, the era of using simple reports for decision making is coming to an end [5]. The main focus is on analyzing key data sets in the context of organizational environment and making accurate predictions [9].

Although there is a huge potential with big data visualization tools [10], the selection of appropriate big data tool is challenging because of varying flexibility, usability and consistency requirements. The evaluation of available big data visualization tools helps to identify the most suitable tool for a given case [3].

Despite the benefits of big data visualization tools for achieving business competitiveness, there is still lack of a research on appropriate methods for assessing and choosing the appropriate big data visualization tool for implementation in a specific situation.

This paper presents a multi-criteria group decision making method for evaluating and selecting big data visualization tools. Intuitionistic fuzzy numbers are used to tackle the subjectiveness and imprecision of the decision making process. The concept based on ideal solutions is applied for producing a relative closeness coefficient value for every big data visualization tool alternative across all selection criteria. An appropriate case is adopted for validating the relevance of the method.

II. The Big Data Visualization Tool Evaluation and Selection Problem

In today's hypercompetitive business environment, organizations are faced with an increasing pressure to use big data to process and analyze quality data for making better and timely decisions [3]. This is further complicated with the sheer volumes of data that need to be processed and the level of detail needed, all at a high speed [4]. As a result, adopting and implementing the appropriate big data visualization tool which is capable of (a) finding and analyzing data quickly, and (b) displaying information in a way that is meaningful and useful for strategic decision making becomes critical in organizations.

Various studies have been conducted on determining the relevant criteria for evaluating and selecting big data visualization tools. For example, traditional methods focus on assessing overall functionality and the system performance [1, 4, 6]. Marakas and O'Brien [11] state that software evaluation criterion includes cost, quality, flexibility, connectivity, security and scalability. Valacich et al. [12] believe that additional criterion vendor feasibility, time to respond when there is a need for support and complexity involved with installation of software. Lynch [13] points out that the software for its maintainability. Meanwhile, Lake and Drake [14] believe that big data visualization tool evaluation should focus on the flexibility and the efficiency of the tool. Rinner [15] believes that level of difficulty involved with using the software, functionality to perform tasks, minimal bugs, and users' willingness to use the software should be considered in software selection. Fuhrmann and Pike [16] state that effectiveness and efficiency of the big data visualization tool are important factors while evaluating and selecting the most suitable tool for adoption. Similarly, Koua et al. [17] point out that effectiveness of the tool performance, usefulness, and appropriateness of the tool as their test measures.

Based on a comprehensive review of the related literature, four most important criteria are identified for evaluating and selecting big data visualization tools including the Costs (C_1), Usability (C_2), Functionality (C_3), and Security (C_4).

Cost (C_1) refers to the total amount required to deploy and use the software. The cost aspect includes licensing cost which is calculated on the basis of number of users [18], hardware upgrades required to install software, recruitment of experts, training users, and ongoing maintenance [2].

Usability (C_2) refers to the ease of use, learnability and efficiency of the big data visualization tool in supporting users. To make better and informed decisions, users may need to combine multiple datasets. In order to navigate to these datasets and combine users may require specialized skills. The big data visualization tools need to be easy to use and learn by the users in their current skillset [19].

Functionality (C_3) of a big data visualization tool refers to the general functional needs of the users [13, 16]. Big data visualization tools are used by the managers at various organization levels and their needs are different. These tools should provide functions to simulate and analyze the data to make predictions and better decisions in a timely manner.

Security (C_4) refers to the level of protection that the big data visualization tool offers in order to protect the data from intruders [19]. The adoption of new technologies without understanding can lead to vulnerabilities. Some of the risks associated with big data visualization tools include unrecognized back doors, default credentials, weaker authentication process for accessing datasets from multiple sources, and incomplete fulfilment of regulatory requirements in relation to log and audit trails [15]. Although big data visualization tools are used by the internal staff, there is a need for comprehensive security mechanism to be put in place to secure the data from intruders [11].

To effectively identify the most appropriate big data visualization tool for a specific scenario, an effective multi-criteria group decision making method is presented below.

III. The Multi-Criteria Group Decision Making Method

The evaluation and selection of appropriate big data visualization tool with respect to the selection criteria discussed as above can be formulated as a multi-criteria group decision making problem.

Evaluating and selecting big data visualization tools involves in (a) determining all available alternatives, (b) identifying the selection criteria, (c) assessing the performance ratings of big data visualization tool alternatives and the weights of the criteria by the decision makers, (d) aggregating the alternative ratings and criteria weights for producing a relative closeness coefficient for big data visualization tool alternatives, and (e) selecting the appropriate alternative [20].

In assessing the performance ratings of big data visualization tool alternatives on multiple criteria, subjective assessments are often made by the decision makers. To represent the subjective assessments of the decision makers, intuitionistic fuzzy numbers [21] are used. This is due to its ability to deal with the subjectiveness and imprecision of the decision making process [20].

Table 1 shows the linguistic terms and their corresponding intuitionistic fuzzy numbers for the decision makers to make subjective assessments about the performance rating of each alternative.

Table 1
Linguistics Terms for Assessing Performance Ratings of Big Data Visualization Tools

Linguistic terms	Intuitionistic Fuzzy Numbers
Very Poor (VP)	(0.02,0.98)
Poor (P)	(0.15,0.75)
Moderately Poor (MP)	(0.35,0.55)
Fair (F)	(0.50,0.35)
Moderately Good (MG)	(0.65,0.25)
Good (G)	(0.75,0.15)
Very Good (VG)	(0.98,0.02)

To obtain the most suitable big data visualization tool alternative, the multi-criteria group decision making method involves:

Step 1: Let $A = (a_1, a_2, \ldots, a_n)$ be the set of alternatives, $C = (c_1, c_2, \ldots, c_m)$, be the set of criteria, and D_k ($k = 1, 2, \ldots, s$) be the set of decision makers. The decision maker D_k provides his/her intuitionistic assessments for each alternative in a form of an intuitionistic preference relation $y_{ij}^k = (\mu_{ij}^k, v_{ij}^k)$, and $0 \le \mu_{ij}^k + v_{ij}^k \le 1, \mu_{ij}^k = v_{ij}^k, v_{ij}^k = \mu_{ij}^k = 0.5$. μ_{ij}^k indicates the degree that the alternative A_i satisfies the criterion C_j whereas v_{ij}^k indicates the degree that the alternative A_i does not satisfy the criterion C_j. Here, we can construct the decision matrix as $D = \lfloor d_{ij} \rfloor_{m \times n}$ of intuitionistic fuzzy value $d_{ij} = (\mu_{ij}, v_{ij})$, where μ_{ij} and v_{ij} are the respective degrees of membership and non-membership of the alternative A_i satisfying the criterion C_j.

$$y_{ij}^k = \begin{bmatrix} \mu_{11}^k, v_{11}^k & \mu_{12}^k, v_{12}^k & \cdots & \mu_{1m}^k, v_{1m}^k \\ \mu_{21}^k, v_{21}^k & \mu_{22}^k, v_{22}^k & \cdots & \mu_{2m}^k, v_{2m}^k \\ \cdots & \cdots & \cdots & \cdots \\ \mu_{n1}^k, v_{n1}^k & \mu_{n2}^k, v_{n2}^k & \cdots & \mu_{nm}^k, v_{nm}^k \end{bmatrix} \tag{1}$$

Step 2: Determine the weights of the criteria. The intuitionistic fuzzy index, $\pi_{ij} = 1 - \mu_{ij} - v_{ij}$ is introduced for determining the decision makers' assessments of the alternative A_i with respect to the criterion C_j. The intuitionistic fuzzy entropy measure developed by Chen and Li [22] is used to determine the weight vector $w = (w_1, w_2, \ldots, w_m)$, where $w_j \ge 0$ and $\sum_{j=1}^m w_i = 1$.

$$w_j^k = \frac{\left(\mu_{11}^k + \pi_{11}^k \left(\frac{\mu_{11}^k}{\mu_{11}^k + v_{11}^k}\right)\right)}{\sum_{k=1}^s \left(\mu_{11}^k + \pi_{11}^k \left(\frac{\mu_{11}^k}{\mu_{11}^k + v_{11}^k}\right)\right)} \tag{2}$$

Step 3: Compute the overall weighted intuitionistic fuzzy performance values r_i of the alternatives for the decision makers by using IFWA operator [23] as:

$$r_i = (\mu_{r_i}, v_{r_i}) = IFWA_w(r_{i1}, r_{i2}, \ldots, r_{in}) = \left(1 - \prod_{i=1}^{n}(1-\mu_{r_{ij}}^{k})^{w_j^k}, \prod_{i=1}^{n}(v_{r_{ij}}^{k})^{w_j^k}, \prod_{i=1}^{n}(1-\mu_{r_{ij}}^{k})^{w_j^k} - \prod_{i=1}^{n}(v_{r_{ij}}^{k})^{w_j^k}\right) \quad (3)$$

Step 4: Determine the intuitionistic fuzzy positive ideal solution α^+ and the fuzzy negative ideal solution α^- based on the weighted fuzzy performance matrix in (3). The positive (or negative) ideal solution consists of the best (or worst) attribute values attainable from all the alternatives [24]. Let J_1 represents the benefit criteria and J_2 represents the cost criteria. The fuzzy positive ideal solution α^+ and the fuzzy negative ideal solution α^- can be determined respectively as:

$$\alpha^+ = (\alpha_1^+, \alpha_2^+, \ldots, \alpha_m^+) = \{\langle([(\max_i \mu_{ij}) | j \in J_1, (\min_i \mu_{ij}) | j \in J_2)], [(\min_i v_{ij}) | j \in J_1, (\max_i v_{ij}) | j \in J_2])\rangle i = 1, 2, \ldots, n\} \quad (4)$$

where:

$$\alpha_j^+ = [\mu_j^+, v_j^+, \pi_j^+].$$

$$\alpha^- = (\alpha_1^-, \alpha_2^-, \ldots, \alpha_m^-) = \{\langle([(\min_i \mu_{ij}) | j \in J_1, (\max_i v_{ij}) | j \in J_2)], [(\max_i \mu_{ij}) | j \in J_1, (\min_i v_{ij}) | j \in J_2])\rangle i = 1, 2, \ldots, n\} \quad (5)$$

where:

$$\alpha_j^- = [\mu_j^-, v_j^-, \pi_j^-].$$

Step 5: Calculate the separation measures. Here, a correlation measure [25] is used for determining the separation measure between alternatives in dealing with intuitionistic fuzzy numbers. The separation measures S_i^+ and S_i^- of each alternative from intuitionistic fuzzy positive-ideal solution α^+ and intuitionistic fuzzy negative-ideal solution α^- can be calculated by using (6)-(7) respectively.

$$S_i^+ = 1 - \frac{1}{n}\sum_{i=1}^{n}\frac{C^+}{1+C^+} \quad (6)$$

where:

$$C^+ = \left|\mu_{A_i} w(x_i) - \mu_A + w(x_i)\right| + \left|v_{A_i} w(x_i) - v_A + w(x_i)\right| + \left|\pi_{A_i} w(x_i) - \pi_A + w(x_i)\right|$$

$$S_i^- = 1 - \frac{1}{n}\sum_{i=1}^{n}\frac{C^-}{1+C^-} \quad (7)$$

where:

$$C^- = \left|\mu_{A_i} w(x_i) - \mu_A - w(x_i)\right| + \left|v_{A_i} w(x_i) - v_A - w(x_i)\right| + \left|\pi_{A_i} w(x_i) - \pi_A - w(x_i)\right|$$

Step 6: Calculate the relative closeness coefficient (RC_i) to the intuitionistic ideal solution α^+ of the alternative A_i as follows:

$$RC_i = \frac{1 - S_i^-}{2 - (S_i^+ + S_i^-)} \quad (8)$$

The larger the relative closeness coefficient RC_i, the better the performance of the alternative A_i is.

IV. AN EXAMPLE

This section presents a problem of evaluating the performance of big data visualization tool alternatives for demonstrating the applicability of the proposed multi-criteria group decision making method discussed above.

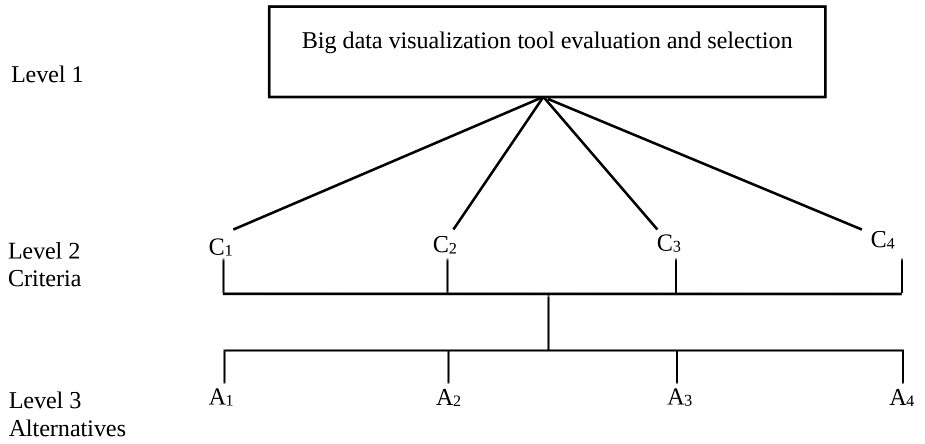
Anonymous Ltd is a global company with around 350,000 employees operating in more than 200 nations worldwide. The company has business interest in electrification value chain from generating power and distributing it to smart grids, medical imaging and laboratory diagnostics. With the launch of Vision 2020, the company tried to understand ways to improve currents, develop products as per customer needs by analyzing already existing data. However, the company could not do that due to multiple architectures and vast amount of data in each database table and the presence of large volumes of unstructured data. In order to make use of the data for improving its product line and at the same time meeting customers' needs, there is a need for the company to identify a big data visualization tool for adoption and implementation.

The evaluation and selection process starts with the formation of a committee involving four decision makers. Four potential alternatives, and four evaluation and selection criteria are identified.

The four potential alternatives include Aster Discovery, Power BI, Tableau, and Looker. Aster Discovery runs on multiple operating systems and contains pre-built library of SQL-MapReduce functions to understand competitive insights and customers' unique needs. These insights help businesses to identify potential failures and take necessary precautions. Microsoft's Power BI has the capability to access data from different data sources, and it is continuously updated with new features and connectors almost on a monthly basis. Microsoft offers good amount of resources to support and enhance user experience [26]. Tableau Desktop comes with online library of samples, allows self-service which make it user-friendly and easy to use. Its menu minimizes the use of code and allows user to make relationships between different data sets to find hidden patterns. The online community helps users to search information, share knowledge and ideas [26]. Looker is a big data visualization tool, which allows access to both SQL and noSQL big data sources. The tool allows users to connect to range of data sources, create their own business data models, and collaborate across the organization [26].

The hierarchical structure of big data visualization tool evaluation and selection problem is shown in Figure 1.

Step 1: Obtain the performance ratings of big data visualization tool alternatives from the decision makers. Table 2 shows the results.



Legend:
C_1: Cost criteria C_2: Usability criteria
C_3: Functionality criteria C_4: Security criteria

A_i ($i = 1, 2, \ldots, n$): Big data visualization tool alternatives.

Figure 1: The hierarchical structure of the performance evaluation of big data visualization tool

Table 2
Performance Ratings of Big Data Visualization Tool Alternatives

Alternatives	Decision makers	Criteria			
		C_1	C_2	C_3	C_4
A_1	D_1	G	G	VG	F
	D_2	VG	G	G	G
	D_3	VG	F	VG	F
	D_4	G	G	G	G
A_2	D_1	F	G	F	MG
	D_2	F	F	F	G
	D_3	MG	G	G	MG
	D_4	MG	MG	MG	G
A_3	D_1	G	G	G	F
	D_2	F	VG	G	G
	D_3	G	G	G	G
	D_4	MG	F	F	F
A_4	D_1	MP	F	MP	F
	D_2	F	MG	F	F
	D_3	F	MP	MG	MP
	D_4	MG	MP	F	MG

Step 2: Based on (2), the weights of the criteria can be calculated as in Table 3.

Table 3
The Criteria Weightings for Each Decision Maker

Decision makers	Criteria weight
D_1	0.3157
D_2	0.3379
D_3	0.2041
D_4	0.1423

Step 3: Compute the overall weighted intuitionistic fuzzy performance values r_i of the alternatives for the decision makers by using IFWA operator (Xu, 2007) as:

$$\begin{bmatrix} (0.728, 0.170, 0.103) & (0.605, 0.292, 0.103) & (0.746, 0.151, 0.104) & (0.769, 0.128, 0.103) \\ (0.718, 0.127, 0.113) & (0.668, 0.231, 0.115) & (0.654, 0.282, 0.184) & (0.746, 0.151, 0.104) \\ (0.562, 0.337, 0.101) & (0.714, 0.226, 0.128) & (0.775, 0.116, 0.141) & (0.596, 0.302, 0.103) \\ (0.526, 0.374, 0.101) & (0.644, 0.254, 0.101) & (0.664, 0.281, 0.212) & (0.626, 0.272, 0.101) \end{bmatrix}$$

Step 4: The intuitionistic fuzzy positive ideal solution α^{+} and the fuzzy negative ideal solution α^{-} can be determined as:

α^{+} : {(0.746, 0.228, 0.062), (0.693, 0.382, 0.158), (0.482, 0.339, 0.182), (0.2973, 0.582, 0.117)}

α^{-} : {(0.518, 0.592, 0.117), (0.383, 0.629, 0.118), (0.572, 0.638, 0.127), (0.462, 0.495, 0.113)}

Step 5: The separation measures S_i^{+} and S_i^{-} of each alternative from intuitionistic fuzzy positive-ideal solution α^{+} and intuitionistic fuzzy negative-ideal solution α^{-} can be calculated by using Equation (6) & (7) respectively. Table 4 shows the results.

Table 4
The Relative Closeness Coefficient of Big Data Visualization Tool Alternatives and their Rankings

Alternatives	S_i^{+}	S_i^{-}
A_1	0.906	0.761
A_2	0.849	0.732
A_3	0.883	0.721
A_4	0.782	0.753

Step 6: The relative closeness coefficient (RC_i) values to the intuitionistic ideal solution α^{+} of the alternative A_i. can be calculated by using (8). It is clear from Table 5 that $A_1 \phi A_3 \phi A_2 \phi A_4$ and therefore A_1 is the most suitable alternative for adoption and implementation.

Table 5
The Relative Closeness Coefficient of Big Data Visualization Tools and their Rankings

Alternatives	Relative Closeness Coefficient	Ranking
A_1	0.714	1
A_2	0.661	3
A_3	0.693	2
A_4	0.637	4

It is evident that the multi-criteria group decision making method is capable of adequately considering the multi-dimensional nature of the problem and effectively handling the subjective and imprecise nature of the decision making process. The proposed method is found to be simple in concept and efficient in computation.

V. Conclusion

Big data visualization tools offer organizations with new ways to dramatically improve their ability to grasp information hiding in their data. The evaluation and selection of the most suitable big data visualization tool for implementation is however challenging due to multi-dimensional nature of the decision making problem, and the subjectiveness and imprecision of the decision making process.

To effectively deal with these issues, this paper has presented a multi-criteria group decision making method for evaluating the performance of big data visualization tool alternatives. Intuitionistic fuzzy numbers are used to tackle the subjectiveness and imprecision of the decision making process. The concept based on ideal solutions is applied for producing a relative closeness coefficient value for every big data visualization tool alternative across all criteria. An example is presented that shows the method is simple and effective for dealing with the big data visualization tool decision making problem.

References

[1] J. Valacich and C. Schneider, *Information Systems Today: Managing in the Digital World*, 6th edn. Australia: Pearson Education Limited, 2011.

[2] C. Snijders, U. Matzat, and U. D. Reips, "Big data: Big gaps of knowledge in the field of Internet science," *Int. J. Internet Sci*., vol. 7, no. 1, pp. 1-5, 2012.

[3] S. Tsuchiya, Y. Sakamoto, Y. Tsuchimoto, and V. Lee, "Big data processing in cloud environments," *FUJITSU Sci. Technol.*, vol. 48, no. 2, pp. 159-168, 2012.

[4] Peer Research, 2012, Big data analytics: intel's it manager survey on how organisations are using big data, Intel, http://www.triforce.com.au/pdf/data-insights-peer-research-report.pdf.

[5] C. L. P. Chen, and C. Zhang, "Data-intensive applications, challenges, techniques and technologies: A survey on big data," *Information Science*, vol. 275, pp. 314-347, 2014.

[6] M. Lnenicka, "AHP model for the big data analytics platform selection," *Acta Inform. Pragnesia*, vol. 4, no. 2, pp. 108-121, 2015.

[7] Dan Sommer, Rita L. Sallam, James Richardson, "Emerging technology analysis: Visualization-based data discovery tools," June 17, 2011.

[8] P. Zikopoulos, D. deRoos, C. Bienko, R. Buglio, and M. Andrews, *Big Data Beyond the Hype: A Guide to Conversations for Today's Data Center*. USA: McGraw-Hill Education, 2015.

[9] D. Loshin, *Big Data Analytics: From Strategic Planning to Enterprise Integration with Tools, Techniques, NoSQL, and Graph*. Waltham: Elsevier, 2013.

[10] J. M. Tien, "Big data: Unleashing information," *J. Syst. Sci. Syst. Eng.*, vol. 22, no. 2, pp. 127-151, 2013.

[11] G. M. Marakas and J.A. O'Brien, *Introduction to Information Systems*. New York: McGrawHill/Irwin, 2013.

[12] J. S. Valacich, J. F. George, and J. A. Hoffer, *Essentials of Systems Analysis and Design*. New Jersey: Prentice Hall, 2012.

[13] C. Lynch, "Big data: how do your data grow?," Nature, vol. 455, pp. 28-29, 2008.

[14] P. Lake and R. Drake, Information Systems Management in the Big Data Era. London: Springer, 2014.

[15] Rinner, C. A Geographic Visualization Approach to Multi-Criteria Evaluation of Urban Quality of Life, Working Paper, VASDS (GIScience 2006)

[16] S. Fuhrmann and W. Pike, *User-centred Design of Collaborative Geovisualization Tools*. In J. Dykes, A.M. MacEachren, and M.-J. Kraak, Exploring Geovisualization. Amsterdam: Elsevier, 2005.

[17] E. L. Koua, A. M. MacEachren, and M. J. Kraak, "Evaluating the usability of visualization methods in an exploratory geovisualization environment," *Int. J. Geogr. Inform. Sci.*, vol. 20, no. 4, pp. 425-448, 2006.

[18] S. S. Kara and N. Cheikhrouhou, "A multi criteria group decision making approach for collaborative software selection problem, *J. Intell. Fuzzy Syst.*, vol. 26, pp. 37-47, 2014.

[19] A. A. Zidan, B. B. Zaidan, M. Hussain, A. Haiqi, M. L. Mat Kiah, and M. Abdulnabi, "Multi-criteria analysis for OS-EMR software selection problem: A comparative study," *Decis. Support Syst*., vol. 78, pp. 15-27, 2015.

[20] S. Wibowo and H. Deng, "Consensus-based decision support for multicriteria group decision making," *Comput. Ind. Eng.*, vol. 66, pp. 625-633, 2013.

[21] K. Atanassov, "Intuitionistic fuzzy sets," *Fuzzy Sets Syst*., vol. 20, pp. 87-96, 1986.

[22] T. Y. Chen and C. H. Li, "Determining objective weights with intuitionistic fuzzy entropy measures: A comparative analysis," *Inform. Sci.*, vol. 180 no. 21, pp. 4207-4222, 2010.

[23] Z. S. Xu, "Intuitionistic fuzzy aggregation operators," *IEEE Trans. Fuzzy Syst*., vol. 15, pp. 1179-1187, 2007.

[24] S. Wibowo and H. Deng, "Multi-criteria group decision making for evaluating the performance of e-waste recycling programs under uncertainty," *Waste Manage.*, vol. 40, pp. 127-135, 2015.
[25] R. Solanki, Q. Lohani, and P. K. Muhuri, "A novel clustering algorithm based on a new similarity measure over intuitionistic fuzzy sets," in *Proc. IEEE Int. Conf. Fuzzy Systems*, IEEE, 2015, pp. 1-8.
[26] N. N. Ramly, F. M. Nor, N. H. Ahmad, and M. H. Aziz, Comparative analysis on data visualization for operations dashboard," *Int. J. Inform. Educ. Technol.*, vol. 2, no. 4, Aug. 2012.