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Big Data (BD), The Internet of Things (IoT), Artificial Intelligence(AI)-driven Advanced Analytics

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Abstract

The Internet of Things (IoT) has continued to be a key development in the tech industry throughout 2017, with many businesses looking to utilise IoT within their key processes and daily tasks. The IoT refers to the world's collection of devices that gather and share information across various industries and sectors. IoT concerns the devices, connectivity, and data. The main purpose of IoT is to create smarter devices that will successfully deliver intellectual insights into those products. It helps in opening a new business prospect. With the onset of numerous smart devices, the intervention of Big Data has become mandatory. It will not only gather proper information but will also capture the data in a particular style. IoT assists in new developments in technology, with the help of AI and big data it is also enabling us to access data in real time. This real-time data has helped to improve key process within business, moving towards a 'smart' and more efficient society. IoT is already one of the key sources for real-time data for AI applications, and enables the decision of AI to be carried out. AI technology is also at the core of predictive analytics and maintenance for IoT. By combining these technologies together costs are reduced and the adoption of new technologies will be done at a much quicker rate. The big data collected from IoT sensors enables AI to make decisions based on potential issues or maintenance work that needs to be fixed on machinery and as a result the business owner is aware well in advance of any technical issues that may need to be addressed. They provide business owners/managers with the data that they need to make key decisions, working towards increasing the efficiency of business processes. Increasing the efficiency of a business will decrease costs, saving businesses considerable amounts of money that can be utilized for other activities. The relationship between IoT, Big Data and AI creates ample opportunity for business to harness exponential growth. A combination of IoT, big data and AI could help futuristic developments and applications to reach new future and they will shape our future.

1. Introduction

Big data and the Internet of Things (IoT) are two hot topics top of mind for business leaders. Together they have been making a significant impact on companies' ability to capture and analyze data to drive business decisions. In today's environment there are many situations where the Internet of Things and big data work hand in hand with each other. However, they evolved as separate technologies and have some differences as well.

Over the previous decade, the Internet of Things (IoT) revolution has had a significant impact on manufacturing, energy, agriculture, transportation, and other industrial sectors. The Industrial IoT (IIoT) is an industry-specific variant of the IoT, which provides an impressive potential for businesses via connected machines, sensors, and applications. It is one of the most exciting technologies now reshaping industrial enterprises, prompting them to modernize their processes, system intelligence via big data processing, and facilities in order to cope with emerging disruptive technologies.

1.1. What is Big Data?

Big data has been an evolving concept since the start of the digital age. Used to describe a huge data set that is defined by three characteristics, known as the three Vs— volume, velocity, and variety—big data differs from other data sets by the size (volume), rate of growth/change (velocity) and the variety of structured, unstructured, and semi structured data within the set.

Big Data is a term that refers to a massive collection of both structured as well as unstructured data that is very difficult to process with traditional techniques. But it is important to analyze business data to get useful insights that help to take strategic business steps. There are many tools that are used by data analysts to produce useful information from unorganized data.

Big Data refers to data which is also too vast or complex to process using usual methods, including what's known as the four V's:

1. Volume: The amount of data collected from a variety of sources.
2. Velocity: The rate of which data is being processed.
3. Variety: The different types of formats of data that are transferring across systems.
4. Veracity: The ability of your Big Data tools and analysis to separate poor quality and high quality data.

Big data is so large and complex that identifying business value from so much information can't be done through traditional methods for processing and analyzing information.

By incorporating technologies like artificial intelligence (AI) and machine learning, more applicable insights can come to light. There are many sources of big data, one of those being data from the Internet of Things (IoT).

1.2. What is AI?

Artificial intelligence, or AI, is technology that enables computers and machines to simulate human intelligence and problem-solving capabilities. AI, also known as deep machine learning, uses algorithms to analyse the data created by the devices in the IoT.

On its own or combined with other technologies (e.g., sensors, geolocation, robotics) AI can perform tasks that would otherwise require human intelligence or intervention. Digital assistants, GPS guidance, autonomous vehicles, and generative AI tools (like Open AI's Chat GPT) are just a few examples of AI in the daily news and our daily lives.

Artificial intelligence encompasses (and is often mentioned together with) machine learning and deep learning. These disciplines involve the development of AI algorithms, modeled after the decision-making processes of the human brain, that can 'learn' from available data and make increasingly more accurate classifications or predictions over time.

1.3. What is IoT?

The Internet of Things is a device that has the ability to transfer data over a network with the least human intervention. IoT devices can be categorized into three parts.

1. Things that collect information and send it
There are devices that have sensors embedded in them and are used as temperature sensors, motion sensors, air quality sensors, soil moisture sensors, etc. These sensors, along with a connection help us to automatically gather data from the environment they are in. To give an example, with the help of soil moisture sensors, farmers get ideas about when their crops need to be watered. These devices have helped people to make better and smart decisions to get favorable outcomes.

2. Things that receive data and act on it
In the system, machines and devices that get data and then act according to that. To give an example for it; a printer receives a document and then prints it. Another, is when the car receives signals from car keys, it opens the door. There are endless examples of this.

3. Things that can perform both these tasks
To give an example for it; a soil moisture sensor that finds out soil moisture and then that data is transferred to the irrigation system through an internet connection. In the system the data about soil moisture, how many crops

are watered, and how well crops actually grow can be gathered and sent to supercomputers that will give the best output after running amazing algorithms.

An IoT system consists of four fundamental components - sensors/devices, data processing, connectivity, and a user interface. Sensors that are embedded in the device collect the data and transfer it to the cloud through internet connectivity. After that, the software processes the data and performs actions such as sending an alert, automatically adjusting the devices, etc.

1.3.1. What is IoT data?

The Internet of Things (IoT) refers to physical objects connected through shared networks. A variety of sensors gather information and share it across systems that can store, manage, filter, and analyze the data. An IoT device can refer to everything from wearables to medical devices to industrial equipment.

The IoT enables companies unprecedented visibility into what is happening across their connected devices in real time. A vast amount of real-time data points are collected from connected IoT devices and transferred across the internet for storage and analysis.

1.4. What is the relationship between IoT and Big Data?

IoT and big data have many overlapping components, and IoT is considered a major source of big data. They were developed independently of one another. As the volume of IoT-generated data increased to the point that conventional storage and analysis methods became inefficient, big data and IoT become more and more interrelated.

In the current environment, the complex data and information gathered by IoT devices can be considered a big data set being gathered in real time. Big data storage and analytics currently help to make sense of the plethora of those real-time data points and provide helpful insights.

A network of devices equipped with electronics and sensors (connected devices) send real-time information to the internet (IoT), where it is compiled and stored into vast data sets (big data) and analyzed to find useful patterns (big data analytics). The collected valuable data is transferred to the cloud through the internet. These piles of data are referred to as big data where artificial intelligence and machine learning are used to generate useful insights. IoT and Big Data share a symbiotic relationship and to understand that connection, the related overall workflow steps are:

1. Companies install sensor-embedded devices to collect and transmit data.
2. A huge amount of data (also called Big Data) is collected in a repository in the form of both structured as well as unstructured.
3. Reports, charts, and other forms of data insights are generated using AI-driven analytics.
4. User devices are used to provide further metrics via settings, scheduling, metadata, and various tangible transmissions.

Big data storage is both the repository and source of data. Adding more and more IoT devices can make AI models complex and collect heavier volumes of big data. The ability to process and perform an action on big data depends on the capacity of hardware that helps to pull out necessary and useful data insights. That is why it is important to invest in efficient hardware and optimized infrastructure design.

2. Material and Method

In the study; an integrated Fuzzy AHP- Fuzzy TOPSIS- Fuzzy VIKOR approaches are used to assess/evaluate BD, IoT, AI-driven Advanced Analytics' factors. In literature Fuzzy Multi Criteria Decision Making Methods (FMCDM) are used in different fields by many researchers [1-23] by using MATLAB program.

2.1. FUZZY MULTI CRITERIA DECISION MAKING METHODS (FMCDM)

In literature Fuzzy Multi Criteria Decision Making Methods (FMCDM) are used in different fields by many researchers and Fuzzy AHP & Fuzzy TOPSIS are also used in many sectors, i.e. IT, to select Big Data (BD), The Internet of Things (IoT), Artificial Intelligence(AI)-driven Advanced Analytics' factors, to evaluate intelligent timetable, to evaluate the criteria for human resource for science and technology, for analyzing customer preferences, to evaluate risk analysis in green supply chain, and to select machine tools.

2.2. Fuzzy AHP Method

Since the standard AHP method does not include the possibility of situations with ambiguity in the estimation, it is possible to upgrade this method with fuzzy approach. This approach is called the Fuzzy AHP method. Instead of one defined value, in the Fuzzy AHP method full range of values that include unsafe attitudes of decision maker should be generated. For that process it is possible to use triangular fuzzy numbers, trapezoidal or Gaussian fuzzy numbers. The Fuzzy AHP method suggests their application directly in criteria pairs comparison matrix. Triangular fuzzy numbers are used in most cases/problems by many researchers in literature because of this reason in the study triangular fuzzy numbers method is used in Fuzzy AHP method. A triangular fuzzy number that is defined in R set can be described as Ñ= (l, n, u) where l is the minimum, n is the most possible and u is the maximum value of a fuzzy case. Its triangular membership function is characterized below which is presented in Figure 1 and in equation (1).

$$\mu\tilde{N}(x) = \begin{cases} (x-l)/(n-l), & l \le x \le n \\ (x-u)/(n-u), & n \le x \le u \\ 0, & x < l \text{ or } x > u \end{cases} \quad (1)$$

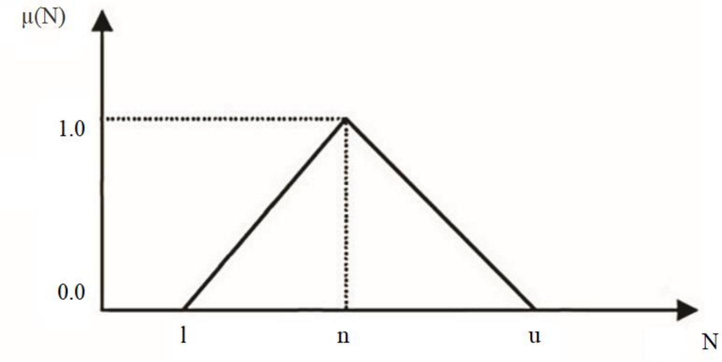

Figure 1. Triangular fuzzy number

Triangular fuzzy number Ñ (shown in Figure 1) can be described as an interval of real numbers where each of them has a degree of belonging to the interval between 0 and 1. Triangular fuzzy number is defined with three real numbers, expressed as l, n and u. In the study the performance of each scenario to each criterion is introduced as a fuzzy number. And in the study the ratings of qualitative criteria are considered as linguistic variables. These linguistic variables can be expressed in positive triangular fuzzy numbers as described in Table 1.

Table 1. Linguistic Variables for the Alternatives

Linguistic Terms-Abbreviation	Linguistic Variables	Triangular Fuzzy Numbers
SDA	Strongly Disagree	(0, 0, 0.15)
DA	Disagree	(0.15, 0.15, 0.15)
LDA	Little Disagree	(0.30, 0.15, 0.20)
NC	No Comment	(0.50, 0.20, 0.15)
LA	Little Agree	(0.65, 0.15, 0.15)
A	Agree	(0.80, 0.15, 0.20)
SA	Strongly Agree	(1, 0.20, 0)

After forming a matrix of fuzzy criteria comparison it should be defined vector of criteria weights W. For that purpose, the following equations/steps were used in the study.

Let X ={x1, x2,..., xm } be an object set, and G={g1, g2,...,gn} be a goal set. N extent analysis values for each object can be obtained as $N_{gi}^{1}, N_{gi}^{2}, \ldots, N_{gi}^{n}$ i= 1,2,…n

Step 1: The values of fuzzy extensions for the i-th object are given in Expression (2);

$$Si = \sum_{j=1}^{n} N_{gi}^{j} \otimes \left[\sum_{i=1}^{m}\sum_{j=1}^{n} N_{gi}^{j}\right]^{-1} \quad (2)$$

In order to obtain the expression $\left[\sum_{i=1}^{m}\sum_{j=1}^{n} N_{gi}^{j}\right]$ it is necessary to perform additional fuzzy operations with n values of the extent analysis, which is represented in Equation (3) and (4);

$$\sum_{j=1}^{n} N_{gi}^{j} = \left(\sum_{j=1}^{n} lj, \sum_{j=1}^{n} nj, \sum_{j=1}^{n} uj\right) \quad (3)$$

$$\left[\sum_{i=1}^{m}\sum_{j=1}^{n} N_{gi}^{j}\right] = \left(\sum_{i=1}^{m} li, \sum_{i=1}^{m} ni, \sum_{i=1}^{m} ui\right) \quad (4)$$

And it is required to calculate the inverse vector above by using Expression (5);

$$\left[\sum_{i=1}^{m}\sum_{j=1}^{n} N_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{m} \text{ui}}, \frac{1}{\sum_{i=1}^{m} \text{ni}}, \frac{1}{\sum_{i=1}^{m} \text{li}}\right) \tag{5}$$

Step 2: While N1 and N2 are triangular fuzzy numbers, the degree of possibility for N2≥N1 is defined as:

$$V(N2 \geq N1) = \text{supy≥x} \left(\min(\mu N_1(x),\ \mu N_2(y)\right) \tag{6}$$

It can be represented in the following manner by Expression (7):

$$V(N2 \geq N1) = \text{hgt}(N2 \cap N1)\ \mu N2(d) \tag{7}$$

$$= \begin{cases} 1, & \text{if } n_2 \geq n_1 \\ 0, & \text{if } l_1 \geq l_2 \\ \frac{(l_1 - u_2)}{(n_2 - u_2)(m_1 - l_1)}, & \text{otherwise} \end{cases} \tag{8}$$

Where d is the ordinate of the highest intersection point D between μN1 and μN2.
To compare μN1 and μN2, values of both, V(N2 ≥ N1) and V(N1 ≥ N2) are needed.

Step 3: The degree of possibility for a convex fuzzy number to be greater than k convex numbers Ni (i=1,2,...,k) can be defined by expression (9);

$$V(N \geq N1, N2,..., Nk) = V[(N \geq N1), (N \geq N2), \dots, (N \geq Nk)] \tag{9}$$
$$= \min V(N \geq Ni=1,2,3,\dots,k$$

Assume that Expression (10) is;

$$d'(Ai) = \min V(Si \geq Sk) \tag{10}$$
for k=1,2,...,n; k ≠ i. So the weight vector is obtained by Expression (11);

$$W' = (d'(A1), d'(A2),..., d'(Am))T \tag{11}$$
where, Ai (i =1,2,...,n) consists of n elements.

Step 4: Through normalization, the weight vectors are reduced to Expression (12);

$$W = (d(A1), d(A2),..., d(An))T \tag{12}$$
where W represents an absolute number.

2.3. Fuzzy TOPSIS Method

The fuzzy TOPSIS calculation most important step is given in Equation (13), i.e. Creating the Decision Matrix; aggregated ratings are calculated by using Equation (13):

$$\tilde{V}ij = \frac{1}{2}\ [\tilde{v}_{ij}^{1} \oplus \tilde{v}_{ij}^{2}\ \oplus \dots\ \tilde{v}_{ij}^{s}] \tag{13}$$

where $\tilde{v}_{ij}^{s}$ is the performance rating value obtained from s-th decision maker.
The basic steps of proposed fuzzy TOPSIS method can be described as follows:

Step 1: In the first step, a panel of decision makers (DMs) who are knowledgeable about supplier selection process is established. In a group that has K decision-makers (i.e. D1, D2, ..., Dk) are responsible for ranking (yjk) of each criterion (i.e. C1, C2, …, Cn) in increasing order. Then, the aggregated fuzzy importance weight for each criterion can be described as fuzzy triangular numbers $\tilde{v}j$ = (aj, bj, cj) for k = 1, 2, …, K and j = 1, 2, …, n. The aggregated fuzzy importance weight can be determined as follows:

$$dj = \min_{k} \{yjk\},\ bj = \frac{1}{K}\sum_{k=1}^{K} yjk,\ cj = \max_{k} \{yjk\} \tag{14}$$

Then, the aggregated fuzzy importance weight for each criterion is normalized as follows:

ṽj = (aj1, bj2, cj3)

where vj1 = $\frac{\frac{1}{dj}}{\sum_{j=1}^{n}\frac{1}{dj}}$, vj2 = $\frac{\frac{1}{bj}}{\sum_{j=1}^{n}\frac{1}{bj}}$, vj3 = $\frac{\frac{1}{cj}}{\sum_{j=1}^{n}\frac{1}{cj}}$ (15)

Then the normalized aggregated fuzzy importance weight matrix is constructed as Ṽ = (ṽ1, ṽ2, …, ṽn)

Step 2: A decision matrix is formed.

$$X = \begin{bmatrix} x11 & x12 & \cdots & x1n \\ x21 & x22 & \vdots & x2n \\ \cdots & \cdots & \vdots & \cdots \\ xm1 & xm2 & \ldots & xmn \end{bmatrix} \quad (16)$$

Step 3: After forming the decision matrix, normalization is applied. The calculation is done using equations 17 and 18.

rij = $\frac{\frac{1}{xij}}{\sqrt{\sum_{i=1}^{m}\frac{1}{xij^2}}}$ for minimization objective, where i = 1, 2, …, m and j = 1, 2, …, n (17)

rij = $\frac{xij}{\sqrt{\sum_{i=1}^{m}xij^2}}$ for maximization objective, where i = 1, 2, …, m and j = 1, 2, …, n (18)

Then, normalized decision matrix is obtained as:

$$R = \begin{bmatrix} r11 & r12 & \cdots & r1n \\ r21 & r22 & \vdots & r2n \\ \cdots & \cdots & \vdots & \cdots \\ rm1 & rm2 & \ldots & rmn \end{bmatrix} \quad (19)$$

Step 4: Considering the different weights of each criterion, the weighted normalized decision matrix is computed by multiplying the importance weight of evaluation criteria and the values in the normalized decision matrix. The weighted normalized decision matrix Ṽ for each criterion is defined as:

Ṽ = [Ṽij]mxn for i = 1, 2, …, m and j = 1, 2, …, n (20)

Where Ṽij = rij X õj
Here Ṽij denotes normalized positive triangular fuzzy numbers.

Step 5: Then fuzzy positive (Ã*) and fuzzy negative (Ã−) ideal solutions are determined as follows:

Ã* = (ṽ1*, ṽ2*, …, ṽn*) where
Ṽj* = $\left\{\max_i(vij1),\ \max_i(vij2), \max_i(vij3)\right\}$ and
Ã- = (ṽ1-, ṽ2-, …, ṽn-) where
Ṽj- = $\left\{\min_i(vij1),\ \min_i(vij2), \min_i(vij3)\right\}$
for i = 1, 2, …, m and j = 1, 2, …, n (21)

Step 6: Then the fuzzy distance of each alternative from fuzzy positive and fuzzy negative ideal solutions are calculated as:

ãi* = $\sqrt{\sum_{j=1}^{n}(\tilde{v}_j^* - \tilde{v}_{ij}^*)}$ and ãi- = $\sqrt{\sum_{j=1}^{n}(\tilde{v}_j^- - \tilde{v}_{ij}^-)}$ i = 1, 2, …, m (22)

Step 7: Then the fuzzy closeness coefficient Ñ is determined as:

Ñi = $\frac{\tilde{a}_i^-}{\tilde{a}_i^* + \tilde{a}_i^-}$ i = 1, 2, …, m (23)

The fuzzy closeness represents the distances to the fuzzy positive ideal solution and the fuzzy negative ideal solution simultaneously.

Step 8: The fuzzy closeness coefficient defuzzified as follows:

Ni = $\sqrt[3]{N_{i1} \cdot N_{i2} \cdot N_{i3}}$ (24)

2.3. Selection of Big Data (BD), The Internet of Things (IoT) and Artificial Intelligence(AI)-driven Advanced Analytics' Criteria: Dimensions and Evaluation Model

BD, IoT, AI-driven Advanced Analytics, i.e. measuring scale, consists of 8 dimensions-main criteria and 41 evaluation factors-sub-criteria are evaluated by decision makers (DMs). A questionnaire was developed following the methodology proposed for the below methods, which was answered by 29 experts/DMs.

In the study 8 main criteria, i.e. Data Storage and Management (C1), Data Visualization (C2), Data Quality (C3), Security and Privacy (C4), Scalability (C5), Interoperability (C6), Data Governance (C7), Real-time Analytics (C8) and 29 related subcriteria are evaluated/assessed by each expert/DM. For the case of prioritization of the criteria, after the aggregation process performed with the answers of the 29 experts, the comparison matrix was obtained. The pairwise comparison matrices for subcriteria and alternatives are calculated.

Subsequently, the normalized pairwise comparison matrix of criteria was obtained. The priority vector and the CR for the criteria were obtained. To obtain the other priorities, the same procedure presented for the criteria was applied. In order to facilitate the calculations; which enters the individual judgments of the experts and generates the local and global preferences of all levels of the hierarchical tree (criteria and subcriteria).

It uses sensor devices and gateway connectivity to derive actionable insights and use them to develop new and advanced services for enhanced productivity. It further improves real-time decision-making, complex operability, and overall experiences. Hereunder, key challenges to BD, IoT, AI-driven Advanced Analytics' main criteria and related sub-criteria are described.

C1. Data Storage and management

Big data continues to grow at an exponentially high rate. As they are today, big data storage systems have a limited amount of space, so it is becoming a significant challenge to manage and store such a large amount of data. The data generated from connected devices increases rapidly; however, most big data systems' storage capacity is limited. Thus, it turns into a significant challenge to store and manage a large amount of data. Therefore, it has become necessary to develop frameworks or mechanisms to collect, save, and handle data.

C2. Data visualization

Data visualization is an important aspect of IoT analysis, aiding in the ability to identify key trends. Data visualization is needed to properly identify and convey the best data insights that can be used to drive business decisions. The data generated by IoT devices is heterogeneous, meaning it comes in a variety of formats: structured, unstructured, and semi structured. While in theory visualizations of data should make it easier to understand trends, when the data comes in so many different formats, a method of visualization becomes more difficult.

C3. Data Quality

Data quality is another significant challenge to IoT-driven analytics success. The data generated by IoT devices is often incomplete, inaccurate, or inconsistent. It is because IoT devices may malfunction or experience network connectivity issues, leading to data loss or corruption. Furthermore, IoT devices may generate data that is irrelevant to the analytics process, leading to noise in the data. To guarantee that the data used for analytics is correct, consistent, and relevant, organizations need to invest in data cleansing & validation processes.

C4. Security and Privacy

IoT devices produce many useful yet sensitive data for an organization. The data may contain much in-depth information also about the company. But as it is always connected to the internet there is a huge issue of security. To guarantee that the data is secure and secret, organizations must implement strong security & privacy measures.

C5. Scalability

IoT analytics involves processing and analyzing massive amounts of data in real-time. It takes a large amount of processing and storage power. Organizations may find it challenging to meet the demand for computational power and storage space as they increase their IoT implementations. Organizations need to have scalable analytics platforms in place to handle the growing volume of data generated by IoT devices.

C6. Interoperability

It means the ability of various devices communicates with one another. Interoperability is crucial in the context of IoT analytics because IoT devices may produce data in different forms and protocols. To guarantee that the data is integrated & analyzed properly, organizations must have systems in place that can handle various data types and protocols.

C7. Data Governance
Data governance refers to the management & control of data assets in an organization. Data governance is crucial in the context of IoT analytics to make sure that the data is appropriately managed and used by legal standards. To ensure that the data created by IoT devices is managed successfully, organizations must have strong data governance frameworks in place.

C8. Real-time Analytics
IoT devices generate data in real time. Real-time data analysis is necessary for every organization that wants to make educated judgments. Real-time analytics can be challenging as organizations need to process & analyze data in real-time to derive insights. All Organizations must have real-time analytics platforms in place. This real-time analytics platform can handle the volume & variety of data IoT devices generate.

2.4. Determining the evaluation criteria weights with Fuzzy AHP Approach

Firstly, each DM practiced pair-wise comparisons of BD, IoT, AI-driven Advanced Analytics' dimensions and evaluation factors by using fuzzy AHP. Using the survey data acquired from these experts, integrated pair-wise comparison matrices are formed by combining all expert opinions. Thus, the pair-wise comparison values are converted to triangular fuzzy numbers and fuzzy pair-wise comparison matrices are created, presented in Table 2.

$$lij = mink\{aijk\} \qquad nij = \frac{1}{K}\sum_{j=1}^{K} b_{ijk} \qquad uij = maxk\{cijk\} \tag{25}$$

Table 2. Fuzzy mutual criteria comparison

	C1	C2	C3	C4	C5	C6	C7	C8
C1	(1, 1, 1)	(3, 5, 7)	(1/5, 1/3, 1)	(1/9, 1/7, 1/5)	(1, 3, 5)	(1/9, 1/7, 1/5)	(5, 7, 9)	(1/9, 1/7, 1/5)
C2	(1/7, 1/5, 1/3)	(1, 1, 1)	(1/7, 1/5, 1/3)	(1, 3, 5)	(1/11, 1/9, 1/7)	(1/5, 1/3, 1)	(1/7, 1/5, 1/3)	(7, 9, 11)
C3	(1, 3, 5)	(3, 5, 7)	(1, 1, 1)	(1, 3, 5)	(5, 7, 9)	(1/7, 1/5, 1/3)	(7, 9, 11)	(7, 9, 11)
C4	(5, 7, 9)	(1/5, 1/3, 1)	(1/9, 1/7, 1/5)	(1, 1, 1)	(3, 5, 7)	(1/9, 1/7, 1/5)	(1/11, 1/9, 1/7)	(1/11, 1/9, 1/7)
C5	(1/5, 1/3, 1)	(1/11, 1/9, 1/7)	(1/9, 1/7, 1/5)	(1/7, 1/5, 1/3)	(1, 1, 1)	(1/9, 1/7, 1/5)	(1/7, 1/5, 1/3)	(1/7, 1/5, 1/3)
C6	(5, 7, 9)	(1, 3, 5)	(3, 5, 7)	(5, 7, 9)	(5, 7, 9)	(1, 1, 1)	(1/7, 1/5, 1/3)	(3, 5, 7)
C7	(1/9, 1/7, 1/5)	(3, 5, 7)	(1/11, 1/9, 1/7)	(7, 9, 11)	(3, 5, 7)	(1/11, 1/9, 1/7)	(1, 1, 1)	(1/7, 1/5, 1/3)
C8	(7, 9, 11)	(1/11, 1/9, 1/7)	(1/11, 1/9, 1/7)	(7, 9, 11)	(3, 5, 7)	(1/7, 1/5, 1/3)	(3, 5, 7)	(1, 1, 1)

After acquiring the fuzzy comparison matrices, importance weights of BD, IoT, AI-driven Advanced Analytics' dimensions; evaluation criteria is calculated by the FAHP method. According to the calculated criteria weights for BD, IoT, AI-driven Advanced Analytics' weights; the most important evaluation dimension/main-criteria is "Real-time Analytics" with 0.237 importance weight, the second important evaluation dimension is "Data Storage and Management" with 0.198 importance weight and the third important evaluation dimension is "Data Governance" with 0.149 importance weight.

2.5. Ranking the alternatives by Fuzzy TOPSIS methods

For the evaluation of BD, IoT, AI-driven Advanced Analytics' factors, Fuzzy TOPSIS approach is conducted with the collected data of DM's surveys/interviews. Primarily, the linguistic variables of the alternatives are created. By the help of criteria weights, Fuzzy-TOPSIS method's steps are performed/completed and BD, IoT, AI-driven Advanced Analytics that affect factors are ranked from the best to the worse. Primarily, the linguistic variables of the alternatives are created.

3. Results

Industry 4.0 is the new heavy trend of the Industry. Also called the 4th Industrial Revolution, it defines the concept of Smart Factory. Behind this concept lies a mix of technologies serving the factory of the future. Connect the machines to the Internet, through the Internet of Things (IIOT), collect the data in the Cloud, and treat them through Artificial Intelligence algorithms, to optimize the Operations, reduce costs through preventive / predictive maintenance. In a general way, to allow an optimized and centralized management of its installations, its equipment, its machines. Sensor technology, Big Data (BD), The Internet of Things (IoT), Artificial Intelligence(AI)-driven advanced analytics are used to optimize operations, such as efficiently balancing supply and demand as customers connect to a smart grid. The usage of IoT in energy production helps to satisfy the energy demands in smart cities in an efficient way. However, a robust digital infrastructure is crucial for the roll-out of an architecture of connectivity and data.

After acquiring the fuzzy comparison matrices, importance weights of BD, IoT, AI-driven Advanced Analytics' dimensions; evaluation criteria is calculated by using Fuzzy method. According to the calculated criteria weights for BD, IoT, AI-driven Advanced Analytics' weights; the most important evaluation dimension/main-criteria is "Real-time Analytics", the second important evaluation dimension is "Data Storage and Management" and the third important evaluation dimension is "Data Governance".

4. Conclusion

Big data and IoT will continue to evolve and play a significant role in an organization's ability to make decisions. IoT in Big Data analytics helps businesses to extract information to get better business insights. Better business insights help in taking better decisions that result in high ROI. Due to an increase in demand for data storage, companies are switching to big data cloud storage which lowers the implementation cost.

The features of Big Data in IoT are reshaping the upcoming generation of the e-health care system and developing an innovative solution in the healthcare field. Big data will now lead to data-driven research instead of hypothesis-driven research. IoT will control and analyze the connection between sensors and existing big data.

In manufacturing companies, due to improper working of equipment and machines, they may end up producing fewer products as they used to do earlier. Installing IoT sensors in the equipment can collect operation data on the machine. The Internet of Things refers to the world's collection of devices that gather and share information across various industries and sectors. In comparison, Big Data offers management and analytical capabilities for huge amounts of data across multiple platforms and systems. However, the interconnectivity between Big Data and Internet of Things means the two technologies share common goals and are predicted to follow a similar trajectory in the future.

Big data analytics help to make sense of the data and information that is gathered by IoT devices. These solutions take the vast, unstructured data that's been collected, and identify ways to organize it into smaller data sets that can give companies insights into how their processes are working, as well as improve decision-making. Big data analytics can provide different types of insights when used with the IoT; namely, descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. Descriptive analytics gives insights into how a connected device is performing in real time. It can be used for anything from locating a connected device, to understanding how that device is used by costumers, to identifying anomalies.

Diagnostic analytics gives insights into the "why" behind descriptive analytics. For a particular connected device, it can help organization understand why it is running in a certain way or why it is producing certain outputs. A very applicable use of big data in IoT is in predictive analytics. This type of analytics utilizes machine learning by analyzing past data and producing probabilities for how the device will function in the future. This is especially beneficial when it comes to the servicing of IoT devices. Using this technology, organizations can anticipate failures or servicing needs before the device stops working. Big data is used in IoT for prescriptive analytics. This type of analysis gives insights into how to impact things that have been observed or predicted.

Using high-tech IoT devices in smart factories leads to higher productivity and improved quality. Replacing manual inspection business models with AI-powered visual insights reduces manufacturing errors and saves money and time. With minimal investment, quality control personnel can set up a smartphone connected to the cloud to monitor manufacturing processes from virtually anywhere. By applying machine-learning algorithms, manufacturers can detect errors immediately, rather than at later stages when repair work is more expensive.

IIoT is used to transfer the data from systems that monitor and control the industrial equipment to data processing systems that cloud computing has shown to be important tools for meeting processing requirements by using Wi-Fi, radio, satellite or cellular networks.

In the study by using Fuzzy method; the calculated criteria weights for BD, IoT, AI-driven Advanced Analytics' weights are as follows: the most important evaluation dimension/main-criteria is "Real-time Analytics", the second important evaluation dimension is "Data Storage and Management" and the third important evaluation dimension is "Data Governance".

IoT analytics can transform various industries, from healthcare to manufacturing. It can take any industry to the highest point. However, there are significant challenges to IoT analytics success that organizations need to overcome. By addressing these challenges, organizations can unlock the full potential of IoT analytics and derive insights that can inform decision-making and drive business growth. Many Big Data tools provide valuable and real-time data to globally connected devices. Big data and IoT examine data precisely and efficiently using suitable techniques and mechanisms. Data analytics may differ with the types of data drawn from heterogeneous sources.

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Conflicts of interest
The authors declare no conflicts of interest.

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